NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

AN ANALYSIS OF DEMAND FORECASTING
EMPHASIZING INVENTORY EFFECTIVENESS

by

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September 1983

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REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

REPORT NUMBER	2. GOVT ACCESSION NO. AD-A138615	3. RECIPIENT'S CATALOG NUMBER
TITLE (and Subtitle) An Analysis of Demand Forecasting Emphasizing Inventory Effectiveness		5. TYPE OF REPORT & PERIOD COVERED Master's Thesis; September 1983
		6. PERFORMING ORG. REPORT NUMBER
AUTHOR(s) Nicholas Martin Sullivan		8. CONTRACT OR GRANT NUMBER(s)
PERFORMING ORGANIZATION NAME AND ADDRESS Naval Postgraduate School Monterey, California 93943		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
1. CONTROLLING OFFICE NAME AND ADDRESS Naval Postgraduate School Monterey, California 93943		12. REPORT DATE September 1983
		13. NUMBER OF PAGES 83
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Inventory Demand Forecasting
Inventory System Effectiveness
Focus Forecasting

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

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DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102-LF-014-6601

#20 - ABSTRACT - (CONTINUED)

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An Analysis of Demand Forecasting Emphasizing Inventory Effectiveness

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MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
September 1983

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ABSTRACT

An analysis is made of the Navy's demand forecasting process and its impact on inventory system effectiveness. The current Navy Uniform Inventory Control Point (UICP) forecasting model is compared with an alternative computer-oriented technique using UICP data. The comparison highlights the presence of highly erratic patterns in the UICP demand data base. Next, a simulation model is exercised to suggest how the UICP demand reporting method might contribute to the variance of recorded demand. The thesis concludes with another simulation indicating the relation of demand forecasting accuracy on each component of total inventory cost. This simulation suggests that, while holding and ordering costs remain relatively insensitive to fluctuations in forecast accuracy, the stockout cost element displays a hypersensitive reaction.

TABLE OF CONTENTS

I. INTRODUCTION

Inventory control is a pivotal activity of any logistics organization. Multi-item inventory systems encompass trade-offs in balancing customer service needs with operating costs. This management task is particularly challenging in the military setting where item availability often affects mission readiness. Clearly, one objective of any inventory doctrine is to succeed in making those decisions which minimize operating costs while providing an acceptable level of service for a forecasted rate of demand. The demand forecasting process and its influence on inventory system effectiveness are the subjects of this study. First, some popular forecasting methods are profiled in terms of six key evaluation measures.

In recent decades, a wide variety of forecasting methods has emerged. Generally, they can be assigned to one of two taxonomies: qualitative or quantitative. Qualitative techniques are regarded as the more subjective of forecasting approaches. Usually conducted in a setting where historical data is unavailable, this class often employs expert opinion in constructing a forecast. The Navy Supply System uses such a method, called Best Replacement Factors, when estimating initial stock levels for a new item of inventory. In contrast, quantitative methods make extensive use of

historical data. There the data serves as input for various types of mathematical models which compute the required forecast. Not surprisingly, advances in computer technology tend to popularize the quantitative-oriented forecasting methods. Rather than spending considerable time synopsizing the more common forecasting techniques, the interested reader is invited to consult the existing literature for supporting detail (see Makridakis and Wheelwright [Ref. 1]). However, it is interesting to classify a few of the widely used techniques in terms of their cost, accuracy, type, applicability, data pattern and time horizon characteristics. Adapted from Wheelwright and Makridakis [Ref. 2], the profile provided by Tables 1 and 2 assists in selecting the most appropriate method for a given forecasting requirement. For example, the widespread appeal, among industry and the military, for the exponential smoothing technique is apparent. To utilize exponential smoothing a manager need have only three data elements: the most recent observation, the most recent forecast and a weighting parameter. This data storage consideration has been of primary importance to multi-item inventory systems where demand forecasts are routinely prepared for several thousand items. Combining such features as low data processing and storage costs together with high applicability, exponential smoothing appears as a rational choice for the Navy's forecasting method. In contrast, the Box-Jenkins technique is not suitable for

TABLE 1.
QUANTITATIVE CLASS

	LAST PERIOD	MEAN	MOVING AVERAGE	EXPONENTIAL SMOOTHING	ADAPTIVE FILTERING	BOX JENKINS	REGRESSION
TIME HORIZON	3 MOS-3 YRS	1-3 MOS	1-3 MOS	1-3 MOS	1-2 YRS	1-2 YRS	> 2 YRS
DATA PATTERN	HTSC	H	H	H	HTSC	HTSC	T
DATA STORAGE	5	30	5-10	3	60	72	30
TYPE	TS,NS	TS,S	TS,NS	TS,NS	TS,NS	TS,S	CL,S
COSTS	LOW	LOW	LOW	LOW	HIGH	HIGH	MED
ACCURACY	MED	LOW	LOW	MED	HIGH	HIGH	MED
APPLICABILITY:							
1- TURNAROUND TIME:	FAST	FAST	FAST	FAST	MODERATE	SLOW	MODERATE
2-INTERPRETATION:	EASY	EASY	EASY	EASY	MODERATE	COMPLEX	EASY

NOTES: THE ABOVE FORECASTING TECHNIQUES ARE CATEGORIZED BY THE FOLLOWING CHARACTERISTICS:

1) TIME HORIZON- THE PERIOD OF TIME INTO THE FUTURE FOR WHICH EACH METHOD IS DESIGNED TO FORECAST.

2) DATA PATTERNS:
(H)-HORIZONTAL- DATA REMAINS RE' ,IVELY STABLE OVER THE TIME HORIZON.
(T)-TREND-DATA EXHIBITS A RATE OF GROWTH OR DECAY OVER TIME.

(S)-SEASONAL-DATA IS INFLUENCED BY SUCH FACTORS AS MONTH OF OF THE YEAR.
(C)-CYCLICAL-DATA SHOWS A LONG TERM OSCILLATION OF UNFIXED DURATION.

3) DATA STORAGE REQUIREMENTS- THE MINIMUM NUMBER OF DATA POINTS WHICH ARE REQUIRED TO BE STORED IN ORDER FOR THE FORECASTING METHOD TO FUNCTION PROPERLY.

4) TYPE- TIME SERIES(TS) MODELS IDENTIFY DEMAND PATTERNS FROM HISTORICAL DATA AND INCORPORATE THESE PATTERNS INTO THE PREPARED FORECAST. CAUSAL(CL) MODELS FOLLOW INFERENTIAL PROCEDUES IN ESTABLISHING FUNCTIONAL RELATIONSHIPS BETWEEN THE DESIRED FORECAST (EG. SALES) AND CAUSATIVE VARIABLES (EG. ADVERTISING, PRICE). NON-STATISTICAL(NS) MODELS SUPPLY ONLY A POINT FORECAST. STATISTICAL(S) PROVIDE NOT ONLY A POINT ESTIMATE BUT ALSO THE INFORMATION NEEDED TO DEVELOP CONFIDENCE INTERVALS FOR THE POINT ESTIMATE.

5) COSTS- A RELATIVE COMPARISON BASED ON THE DEVELOPMENTAL, STORAGE,AND COMPUTER OPERATING COSTS ASSOCIATED WITH EACH MODEL.

6) ACCURACY- RELATIVE COMPARISON BASED ON EACH MODEL'S ABILITY TO PREDICT BOTH UNDERLYING DATA PATTERNS AS WELL AS TURNING POINTS IN THE DATA PATTERN.

7) APPLICABILITY- HOW EACH FORECASTING METHOD CAN BE APPLIED IN TERMS OF: 1) THE TIME REQUIRED TO PREPARE A FORECAST; 2) THE EASE OF INTERPRETATION OF MODEL OUTPUT.

TABLE 2.
QUALITATIVE CLASS

	DELPHI	S-CURVE	HISTORICAL ANALOGIES	RELEVANCE TREES
TIME HORIZON	>2 YRS	>2 YRS	>2 YRS	>2 YRS
DATA PATTERN	N/A	N/A	N/A	N/A
DATA STORAGE	0	0	0	0
TYPE	CL,NS	TS,NS	CL,NS	CL,NS
COSTS	MED	MED	MED	HIGH
ACCURACY	MED	MED	MED	HIGH
APPLICABILITY:				
1- TURNAROUND TIME:	MODERATE	MODERATE	MODERATE	SLOW
2- INTERPRETATION:	EASY	MODERATE	EASY	MODERATE

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UICP use. Although it offers great accuracy, the Box-Jenkins method's excessive data processing and data storage requirements render its costs prohibitive.

However profiled in terms of these six factors, the best measure of effectiveness for a forecasting method is the economic benefit it provides to its dependent inventory control system. The identification of a method which incurs low data processing costs while contributing to minimal holding and stockout costs remains the goal of the inventory forecaster. This notion will be pursued further.

Before examining the cost effects of forecast accuracy several issues will be analyzed. The following chapter reviews the forecasting model currently installed at one of two Navy Inventory Control Points, the Navy Ships Parts Control Center (SPCC), and also introduces an alternate computer-oriented model called, "Focus Forecasting." Chapter III reveals that items having erratic demand patterns constitute an appreciable portion of the ICP's inventory population. Chapters IV and V identify both the cost effects and some sources of extreme variability in the UICP demands. Lastly, Chapter VI uses a computer simulation to examine the cost effects of forecast accuracy.

II. TWO FORECASTING MODELS

A. EXPONENTIAL SMOOTHING

As previously indicated, exponential smoothing satisfies the requirements for a forecasting procedure which demands low computer storage and run time. Accordingly, the UICP model utilizes a refined version of exponential smoothing in establishing, among other things, the parameters for the leadtime demand distributions. Employing a modification of the continuous-review inventory formulation found in Hadley and Whitin [Ref. 3], the UICP model applies the forecasted leadtime demand in determining both economic order quantities and reorder points.

Exponential smoothing methods, originally advocated by Brown [Ref. 4], are a geometrically weighted sum of all past demands with the greatest weight applied to the most recent observation. Mathematically a forecast is calculated as:

NEW FORECAST = LAST FORECAST + WEIGHT (LAST OBSERVATION - LAST FORECAST)

Notationally this may be stated as

$$F_{t+1} = F_t + \alpha(D_t - F_t); \quad t \geq 1$$

which reduces to

$$F_{t+1} = \alpha D_t + (1-\alpha) F_t; \qquad t \geq 1 .$$

Here α is known as the smoothing weight and is normally assigned a value between zero and one. The accuracy of the exponentially smoothed forecast depends strongly on the chosen α value. In normal practice, the α smoothing constant is either selected arbitrarily or suggested through exhaustive sensitivity analyses. With D_t again denoting the actual demand observation recorded in period t, the above equation can be represented in recursive form as:

$$F_{t+1} = \alpha D_t + \alpha(1-\alpha) D_{t-1} + \alpha(1-\alpha)^2 D_{t-2} + \alpha(1-\alpha)^3 D_{t-3} + \ldots$$

From this recursive form it is easily seen how exponential smoothing dilutes the effect of the older observations. The data-processing simplicity of this technique is evident since one stored value, F_{t+1}, replaces the entire block of t demands. One point of concern can be the initial or seed value for F_t. Since a F_t value is needed before the next F_{t+1} forecast is prepared, a seed value must be found to initialize the process when t = 0. Several solutions to the seed selection problem are available. Some of the simpler solutions recommend using the first observation as a seed or dividing the time series data into two parts with the first part reserved for initial estimation purposes (average, least squares estimation, etc.). In practice the seed problem

is only of theoretical concern. (See Makridakis and Wheelwright [Ref. 1].) Generally, the forecasting process will be in operation lor.s enough to suppress any dependency on the seed.

The simple form of exponential smoothing described above is essentially an approximation of a moving average forecasting process. An inherent drawback of this model is that it is relatively insensitive to recent trend changes. This weakness, left uncorrected, would frequently result in biased forecasts. Recognizing this limitation, the UICP model refines the process by incorporating two types of demand filters. (See Basic Inventory Manager's Manual [Ref. 5].) First a trend test is conducted to detect sustained ($\geq$ 3) changes from the underlying pattern. The trend statistic, TR, is a ratio test consisting of:

$$TR = \frac{2(\text{SUM OF LAST TWO OBSERVATIONS})}{(\text{SUM OF LAST FOUR OBSERVATIONS})}$$

A trend is considered present when either:

$$TR > 1.1 \quad \text{and} \quad (D_t \geq F_t, \;\; D_{t+1} \geq F_{t+1})$$

or

$$TR < 0.9 \quad \text{and} \quad (D_t \leq F_t, \;\; D_{t+1} \leq F_{t+1})$$

When either of these trend conditions exist, the smoothing constant is modified from its usual .10 value to a new, "heavier" weight of .30. This causes the next forecast to be more directly influenced by the most recent observation. Next, a second filter is used to check for outlier observations. This filter computes a control tolerance band around F_t using multiples of mean absolute deviation (MAD), the average of the absolute difference between actual and forecasted demand. For further discussion on the exact UICP use of MAD see the Basic Inventory Manager's Manual [Ref. 5]. If the most recent demand observation lies within a band of width 7.5 MAD about F_t, the process is considered in control and no modifications are necessary. If a single out-of-control condition has been indicated by the filter, the outlier demand is ignored and the forecast is left unchanged, i.e., $F_{t+1} = F_t$. Further, if two successive demand observations lie on the same "side" (high or low) of the tolerance band, the next forecast is calculated as the average of the two cohort outlier demands, i.e., $F_{t+1} = .5(D_{t-1} + D_t)$. This condition is known as a "step increase/decrease."

This completes the discussion of the SPCC exponential smoothing model. Next, "Focus Forecasting" is introduced.

B. FOCUS FORECASTING

Focus forecasting is a new forecasting approach first advocated by Smith [Ref. 6]. His concept requires the

dynamic simulation capabilities of modern computers in preparing each forecast. The methodology is somewhat inviting due to its overriding simplicity. Focus forecasting emphasizes a straightforward, flexible design in acquiring user understanding and confidence. The requirement for transparent forecasts which are derived from simple strategies and which capitalize on recent advances in computer technology motivated Smith in creating the concept. The mechanics of the process consist of four operations: backforecasting, selection, application and repetition. First, employing a dynamic evaluation routine, the computer identifies from a corpus of simple strategies the one which would have best forecasted the preceding period's demand. Next, this selected strategy is used in preparing the upcoming period's demand forecast. Lastly, the process is repeated until "optimal" strategies have been identified and applied for each inventory item. Recent strides in computer technology make possible Smith's procedure which, when implemented for large inventory systems, requires great internal processing speed. For clarity, a conceptual example of the focus forecasting algorithm is presented.

- Item Demand History:

Time Period (Quarters):	1	2	3	4	5	6	7	8
Units Demanded (D_t):	596	388	527	259	270	363	357	250

Required: F_t where $t = 9$.

- Strategy Corpus:

  STRAT(1)--"LAST PERIOD THIS YEAR"

$$F_t = D_{t-1}$$

  STRAT(2)--"AHEAD/BEHIND THIS QUARTER LAST YEAR"

$$F_t = (D_{t-1} \times D_{t-4})/D_{t-5}$$

- Routine:

  Step 1--Backforecast for t-1, i.e., compute F_{t-1}

$$\begin{aligned} STRAT(1) &= F_8 = D_7 \\ &= 357 \\ STRAT(2) &= F_8 = (D_7 \times D_4)/D_3 \\ &= (357 \times 259)/527 \\ &= 175 \end{aligned}$$

  Step 2--Select item--"optimal" strategy

$$\begin{aligned} DIFF(1) &= ABS(D_8 - STRAT(1)) \\ &= ABS(250 - 357) \\ &= 107 \\ DIFF(2) &= ABS(D_8 - STRAT(2)) \\ &= ABS(250-175) \\ &= 75 \end{aligned}$$

  since 75 < 107 item "optimal" strategy is STRAT(2).

  Step 3--Apply selected strategy

$$F_t = (D_{t-1} \times D_{t-4})/D_{t-5}$$

$$F_9 = D_8 \times D_5/D_4$$
$$= (250 \times 270)/259$$
$$= 261$$

Step 4--Repeat for next item

(go to step 1)

Smith has implemented a seven-strategy version for a major commercial wholesaler of hardware. There the system prepares demand forecasts for over 100,000 items each month. Smith maintains that his procedure of adapting a series of forecasting approaches to item demand will significantly outperform a single-formula process such as the UICP exponential smoothing model. Before this claim is examined, we briefly outline how focus forecasting might be successfully applied to military use--specifically leadtime demand parameterization.

As an initial, albeit crude, attempt at implementation, six simple strategies derived from three general forecasting categories are to be used. The first two strategies come from the so-called, "Naive" class. These are the previously described "last period this year" method and its cohort, "this period last year." (Notationally--STRAT(1) = D_{t-1}; STRAT(2) = D_{t-4}.) The first method acknowledges trend; the second seasonality. The next three strategies are selected from the class of moving averages, all of which model horizontal demand patterns. The moving averages will be computed

as 2, 4 and 8 period averages. (Notationally--STRAT(3) = $.5(D_{t-1} + D_{t-2})$; STRAT(4) = $.25(D_{t-1} + \ldots + D_{t-4})$; STRAT(5) = $.125(D_{t-1} + \ldots + D_{t-8})$.) Finally, as proposed by Bates and Granger [Ref. 7], a composite forecast is adapted in order to improve forecast accuracy by capturing information from each forecast strategy. (Notationally--STRAT(6) = .2(STRAT(1) + ... + STRAT(5))).

The next chapter compares the UICP exponential smoothing and focus forecasting models using empirical data.

III. MODEL COMPARISON

A. EMPIRICAL DATA

To evaluate the two forecasting models under consideration, a nine year demand history was retrieved. The Operations Analysis Department at the Navy Fleet Material Support Office (FMSO) followed a stratified sampling procedure in preparing a random sample of 522 repairable and 4530 consumable items. Each of the 5052 items was represented by one master data record followed by several subrecords. The master record contains descriptive information such as national stock number, replacement price, etc. Each subrecord contains demand quantity and demand Julian date information. The complete record format can be found in [Ref. 8]. For convenience, sequential dates ranging from 0001 to 3285 replaced the Julian dates for the nine year period. A FORTRAN computer program aggregated the subrecord demand data into 36 quarterly "buckets." (A complete listing of the principal FORTRAN IV source codes used in this thesis is available in Appendix A). Negative demand quantities were assumed to be the result of customer cancellations. When negative demands were encountered, the quarterly demand balance was appropriately reduced. When adjusting for such cancellations, however, the quarterly balances were forced to maintain strictly non-negative values.

B. EVALUATION CRITERIA

One aim of a forecasting process is the minimization of the total forecast error incurred over time. When stochastic demand rates are involved, a natural assumption is that superior inventory control requires very accurate forecasting. This assumption seems reasonable since, in the extreme case where demand rates are deterministic, existing inventory models achieve zero stockout cost and optimal ordering and holding costs. (See [Ref. 3].) Unfortunately, forecast accuracy lacks an absolute standard of measurement. Instead, the decision-maker is free to choose from a wide variety of evaluation schemes. Conceivably, each scheme could rank the forecasting models differently. This section briefly describes the evaluation criterion selected for comparing the focus forecasting and SPCC exponential smoothing models. Chapter VI presents an alternate effectiveness measure--the cost impact of forecast error.

Traditionally, squared forecast errors (SFE) have been a useful determinant of accuracy with mean squared error (MSE) serving as a popular choice. MSE is defined mathematically as:

$$MSE = \frac{1}{n} \sum_{t=1}^{n} (F_t - D_t)^2$$

MSE is functionally related to variance and also enjoys wide acceptance as a measure of "closeness." Squaring a

forecast error provides two advantages. First, the algebraic sign of the error is disregarded. This avoids distortion caused by offsetting positive and negative errors. Second, the squaring operation penalizes large forecast errors.

SFE measures are not without drawbacks. For example, what is the preference ordering for two models posting MSE's of 81.49 and 75.19? The second forecasting model appears more accurate but with what significance? Another drawback of MSE is that it does not facilitate comparison across different time intervals. These limitations notwithstanding, three SFE measures will be used: mean, standard deviation and the 90th quantile.

The next effectiveness criterion is designed to check for biased forecasts. Bias distorts forecast accuracy through systematic overforecasting or underforecasting. Several statistics drawn from the distribution of forecast errors help identify an unbiased forecasting model. Any reasonably unbiased model will exhibit two attributes. First for large samples, the forecast errors should have a mean of zero. Second, as an indication of symmetry the median forecast error should approximate its mean. The standard deviation of forecast errors will also be included as a measure of dispersion.

A third important consideration in determining forecast accuracy is how well the model performs for the higher

priced inventory. The manager may benefit little from a model providing low bias and dispersion for only the lower priced items. Therefore, forecast errors will be weighted by item replacement price (PWFE) and tested by the three bias measures described above.

Finally, the correlation between forecasted and actual demands is considered. Often two time series are closely related but not in a statistically dependent sense. The correlation coefficient can measure the strength of the linear relationship between two random variables. Also known as Pearson's product moment coefficient and denoted by r, the correlation coefficient is defined as:

$$r = \frac{\sum_{t=1}^{n} (D_t-\bar{D})(F_t-\bar{F})}{\left(\sum_{t=1}^{n} (D_t-\bar{D})^2 \sum_{t=1}^{n} (F_t-\bar{F})^2\right)^{1/2}}$$

where $\bar{D}$ is mean actual demand; $\bar{F}$ is mean forecasted demand; $r \in [-1,1]$.

A forecasting mechanism which parallels changes in the demand pattern is highly desirable. A high r value would typically indicate such behavior although it must be regarded with caution. For example, a high r value may indicate a spurious relationship caused by chance or by the elimination of a third explanatory variable. Nonetheless, r remains a recognized measure of the tracking capability of a forecasting model.

In summary, four classes of evaluation criteria will be reported:

1) SFE--(MSE,SD,P_{90}) as measures of closeness,
2) FE--(mean,median,SD) as measures of bias,
3) PWFE--(mean,median,SD) as measures of price weighted bias,
4) CORRE--(r) as a measure of association and direction.

Before reporting the results of the model comparison, some amplifying remarks are offered. The SPCC exponential smoothing model was translated into the ES FORTRAN source code found in Appendix A. This code contains all of the provisions described in Chapter II. The seed values were computed as the average of the first four quarters of demand. To dilute the effect of this selection, the program was stabilized over demand years two and three. The demands representing years four through seven were examined in terms of the selected effectiveness measures. The FOCUS FORTRAN source code represents the previously described focus forecasting model. For the six simple forecasting strategies selected, neither initialization nor stabilization was required. To preserve an equal footing, however, demand years four through seven were again used for comparison to the SPCC model. Note that each strategy must require no more than eight quarters of demand history. This constraint is imposed since UICP data files presently access only two years of demand history. Also note that the FOCUS program

lacks a high demand filter. Some basic filters are offered by Smith but none were coded for the initial trial run.

The tables which follow show the results of testing the SPCC exponential smoothing and focus forecasting models using four years of actual UICP demand history. To facilitate model comparison between repairable and consumable inventory items, the demand history was separated into two populations. These tables record each forecasting model's performance in terms of the previously described forecasting effectiveness measures.

C. FINDINGS

The results in Tables 3 and 4 do not suggest a clear modelling preference. However, they do reveal some unexpected results which led to a redirection of this study. First the MSE and SFE P_{90} values indicate that the presence of large outliers severely distorts MSE. The use of P_{90} as a more stable measure does not indicate a significant difference in model closeness. Second, both models succeed in providing unbiased forecasts with the focus forecasting model generally producing a smaller price weighted forecast error. Next, there does not appear to be any significant difference in the model's tracking ability as measured by r. However, both models appear more successful at tracking consumables than repairables.

TABLE 3

Repairable Items--Sample Size 2088 (522 × 4 Quarters)

		Exponential Smoothing				Focus Forecasting			
	Model Year:	4	5	6	7	4	5	6	7
Class:	Measure:								
Squared Error	MSE	133.5	73.1	48.7	81.5	104.9	43.5	67.4	45.2
	SD	2727.2	1962.3	625.9	1337.6	1305.6	503.1	773.9	1155.6
	P_{90}	8.2	8.4	7.6	8.1	12.3	9.0	6.3	9.0
Forecast Error	Mean	0.0	0.0	0.1	0.3	0.0	0.0	0.0	0.5
	Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	SD	11.6	8.6	7.0	9.0	10.2	6.6	8.2	8.7
Price Weighted Forecast Error	Mean ($\times 10^2$)	5.4	7.0	17.1	24.2	10.7	6.8	14.8	15.6
	Median ($\times 10^0$)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	SD ($\times 10^3$)	15.5	12.3	20.0	29.2	17.5	23.0	22.3	31.9
Correlation	r	.25	.41	.50	.50	.23	.45	.55	.51

TABLE 4

Consumable Items--Sample Size 18120 (4530 × 4 Quarters)

		Exponential Smoothing				Focus Forecasting			
	Model Year:	4	5	6	7	4	5	6	7
Class:	Measure:								
Squared Error	MSE ($\times 10^2$)	49.0	45.1	88.6	121.8	49.3	126.3	85.7	103.9
	SD ($\times 10^4$)	38.5	38.3	76.4	53.3	31.0	122.1	87.5	51.1
	P_{90} ($\times 10^0$)	10.6	11.0	12.0	16.0	12.3	10.6	12.3	16.0
Forecast Error	Mean	0.6	0.4	1.3	3.8	0.7	−0.8	1.2	3.0
	Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	SD	70.0	67.2	94.1	110.3	70.2	112.4	92.6	101.9
Price Weighted Forecast Error	Mean	22.4	17.4	14.1	37.8	20.6	11.2	8.7	33.7
	Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	SD	12.0	7.2	7.4	12.1	11.1	8.6	9.8	13.4
Correlation r		.98	.98	.98	.99	.98	.95	.98	.97

The next originally planned task was to fine tune focus forecasting using high demand filters and inject alternate forecasting strategies for subsequent trial runs. However, this task was interrupted when demand patterns, such as the three actual demand histories shown below, were observed.

DEMAND HISTORY

ITEM \ QUARTER	1	2	3	4	5	6	7	8
1	76	5843	18798	15	58	746	19	0
2	6	2	6	78	0	8	10	3
3	15	44	64	7	100	604	130	2239

It was startling to observe a significant amount of variability in both the repairable and consumable demand histories. To gain a rough estimate of the magnitude of this dispersion the average coefficient of variation (STANDARD DEVIATION [D]/ EXPECTED VALUE [D]) was computed. The two data sets recorded average coefficients of:

$$\text{Repairable} \quad - \quad \overline{\text{COEFF VAR}} = 3.80$$

$$\text{Consumable} \quad - \quad \overline{\text{COEFF VAR}} = 3.58$$

Since coefficients of variation greater than 1.0 are usually regarded as an indication of excessive dispersion [Ref. 1], it appears that the demand histories profiled above are the rule rather than the exception. Recognition of the data's extreme variability is further suggested by SPCC's 1980

change to their model's high demand filter. The control tolerance band was revised from its previous $F_t \pm 3.75$ MAD to a widened range of $F_t \pm 7.50$ MAD. These erratic demand patterns challenge the foundation of those inventory models (such as SPCC's) which assume a stationary demand rate from quarter to quarter. Thus, two new research directions were suggested: (1) identify the causes of erratic UICP demand and (2) assess the cost impact of forecast inaccuracy on the type of inventory models implemented by the ICP's.

IV. THE ECONOMIC BENEFITS FROM VARIANCE REDUCTION

Before studying the causes of erratic UICP demands, it is proper to first identify the marginal benefits which can be derived from reducing demand variance.

The stochastic backorders model developed in [Ref. 3] contains three cost elements: order, holding and stockout costs. Mathematically these are represented in the total annual variable cost equation as:

$$K(Q,r) = \lambda A/Q + IC(Q/2 + r-\mu) + \pi\lambda/Q[\int_r^\infty xh(x)dx - rH(r)],$$

or

$$TVC = ORDER + HOLDING + STOCKOUT\ COSTS$$

For our purposes, $K(Q,r)$ is assumed to be both differentiable and jointly convex in Q and r. Under these assumptions, the values Q^* and r^* which minimize $K(Q,r)$ are determined by the methods described below. It should be noted, however, that joint convexity depends on the particular distribution of $h(x)$. Brooks and Lu [Ref. 9] and Veinott [Ref. 10] show that $K(Q,r)$ can be nonconvex when $h(x)$ is non-decreasing and $r < \mu$. (Nonconvexity may lead to a failure in the optimization technique which follows.)

Under joint convexity the optimal values Q^*, r^* (where $0 < Q^* < \infty$, $0 < r^* < \infty$) must satisfy the equations:

$$\frac{\partial K}{\partial Q} = 0 = \frac{-\lambda}{Q^2}(A + \pi\bar{n}(r)) + \frac{IC}{2}$$

$$\rightarrow Q^*(r) = [2\lambda(A + \pi\bar{n}(r))/IC]^{1/2}$$

$$\frac{\partial K}{\partial r} = 0 = \frac{\pi\lambda}{Q}[\frac{\partial}{\partial r}(\int_r^\infty (x-r)h(x)dx)] + IC$$

$$= \frac{\pi\lambda}{Q}[-H(r)] + IC \quad \text{(using Leibniz's Rule)}$$

$$\rightarrow H(r^*(Q)) = QIC/\pi\lambda$$

(note π must be sufficiently large such that $H(r^*(Q)) < 1$). Computing a numerical solution for $Q^*(r)$ and $r^*(Q)$ poses a problem of composite dependency. That is to solve for Q^* we need to know $\bar{n}(r)$ and thus r. Secondly, to solve for r^* requires a knowledge of Q. As a practical and accurate alternative, a five-step numerical iteration routine is invoked.

1) Check for a unique solution, i.e., if

$$[2\lambda(A+\pi\mu)/IC]^{1/2} < \pi\lambda/IC \rightarrow \text{unique } Q^*, r^*$$

2) Assume $\bar{n}(r) = 0$ and starting with $i = 1$,

$$\text{compute } Q_i = [2A\lambda/IC]^{1/2}$$

3) Compute r_i from $H(r_i(Q_i)) = Q_i IC/\pi\lambda$ by consulting "tail" distribution tables of $H(x)$

4) Compute Q_{i+1} by using r_i to find $\bar{n}(r_i)$, i.e., compute $Q_{i+1} = [2\lambda(A+\pi\bar{n}(r_i))/IC]^{1/2}$

5) Repeat steps 3) and 4) until Q_{i+1}, r_{i+1} converge on Q_i, r_i.

To determine the effect of demand variance (σ^2) on K requires a knowledge of $\partial K/\partial\sigma$ where

$$K(Q,r,\sigma) = \lambda A/Q(r,\sigma) + IC(Q(r,\sigma)/2 + r(\sigma)-\mu) + \pi\lambda\bar{n}(r,\sigma)/Q(r,\sigma)$$

Unfortunately, developing a determinant form of $\partial K/\partial\sigma$ is more complicated than the earlier task of solving for Q* and r*. The complication stems from the composite dependency among σ, Q and r. That is, $\partial K/\partial\sigma$ depends on $\partial\bar{n}(r)/\partial\sigma$ which depends on r which in turn depends on Q. For example, if the leadtime demand distribution is assumed normal with mean μ and standard deviation σ then

$$\frac{\partial\bar{n}(r)}{\partial\sigma} = \frac{\partial}{\partial\sigma}\left[\int_r^{\infty}(x-r)\,\phi(x,\sigma)\,dx\right]$$

$$= \int_r^{\infty} - \frac{\partial r}{\partial\sigma}\,\phi(x,\sigma)\,dx + \int_r^{\infty}(x-r)\,\frac{\partial\phi(r)}{\partial\sigma}\,d\sigma$$

where $\phi(x,\sigma) = (1/\sqrt{2\pi}\sigma)\exp[(x-\mu)^2/2\sigma^2]$ and r is the solution to $H(r,\sigma) = ICQ(r,\sigma)/\pi\lambda$.

To remedy this complication and to graphically illustrate the relation between K and σ, a sensitivity analysis was

conducted using the FORTRAN program entitled INVENTOR. For a set of input parameters which remained fixed throughout the analysis 1000 realizations of σ were used in computing the three cost elements of K. The particular set of input parameters ($A = 500$, $\lambda = 180$, $IC = 15$, $\pi = 500$, $\mu = 90$) was selected to ensure joint convexity in Q and r. The 1000 values of σ are equally spaced over the interval [10,350]. The upper and lower limits of this interval were selected to reflect the coefficients of variation found in the UICP sample. The upper limit of this range was specified to coincide with the average coefficient of variation (approximately 3.80) reported in Chapter III (i.e., $350 \simeq 3.80 \times 90$). Graphical representations of the sensitivity analysis are found in Figure 1-4. To facilitate comparison of the changes in each of the four cost categories, each axis shown in Figures 1-4 was normalized in the following manner:

(1) Ordering, holding, stockout and total variable costs were each computed 1000 times for the 1000 different values of σ.

(2) The first value of each cost (where $\sigma = 10$) was used as a basis value.

(3) Each of the four sets of the 1000 cost values was then divided by its respective basis to produce the vertical coordinates used in the graphs. The 1000 σ values were normalized by dividing each by $\sigma = 10$ thereby producing the horizontal coordinates found in the graphs.

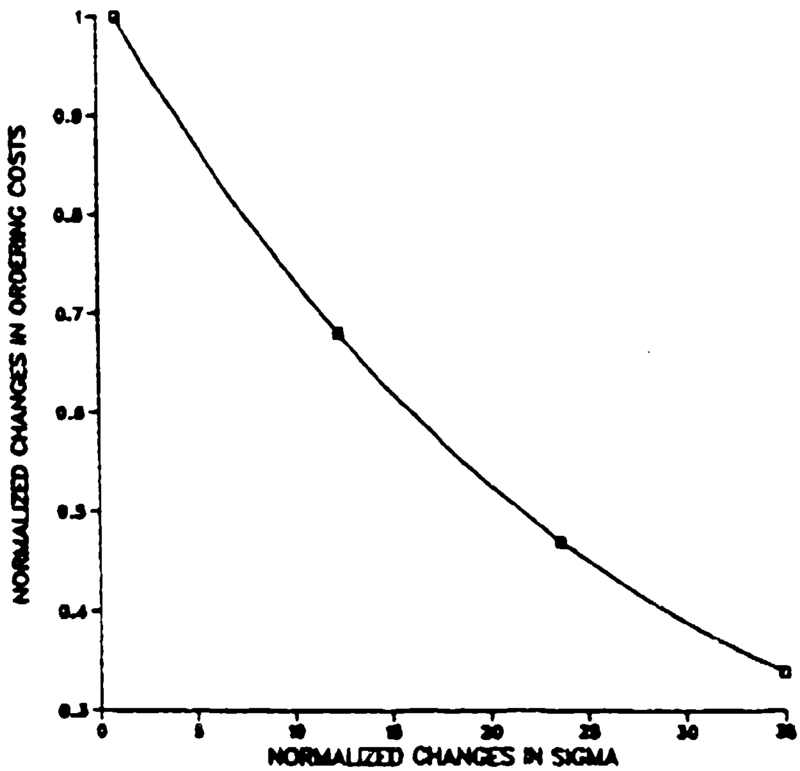

Figure 1. Ordering Cost Sensitivity to Sigma

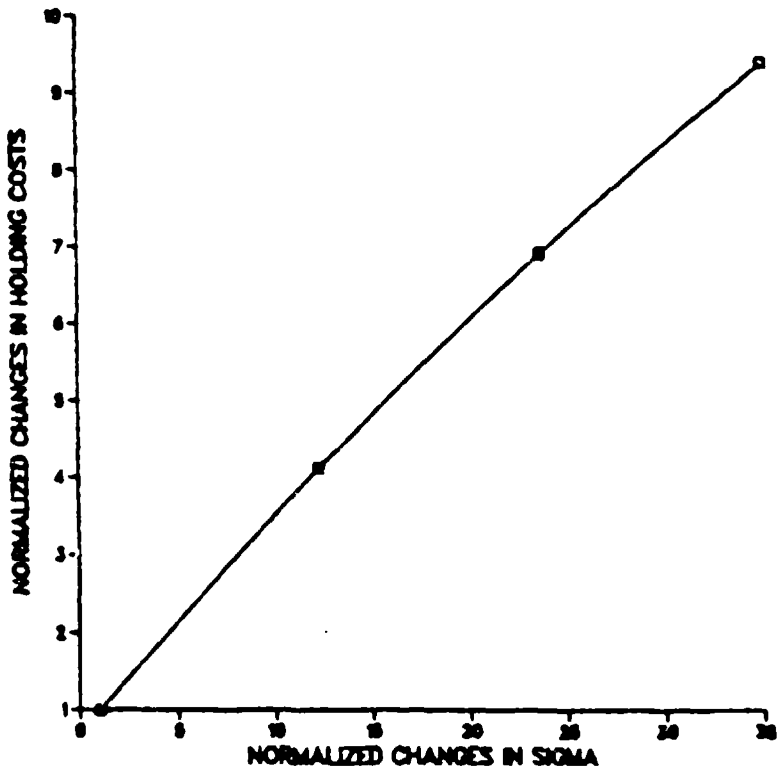

Figure 2. Holding Cost Sensitivity to Sigma

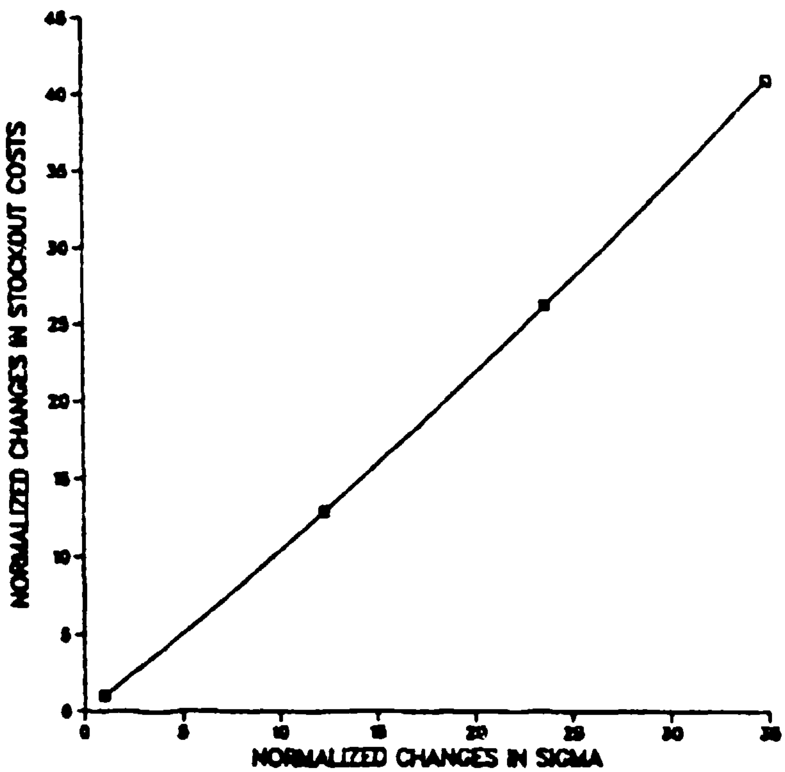

Figure 3. Stockout Cost Sensitivity to Sigma

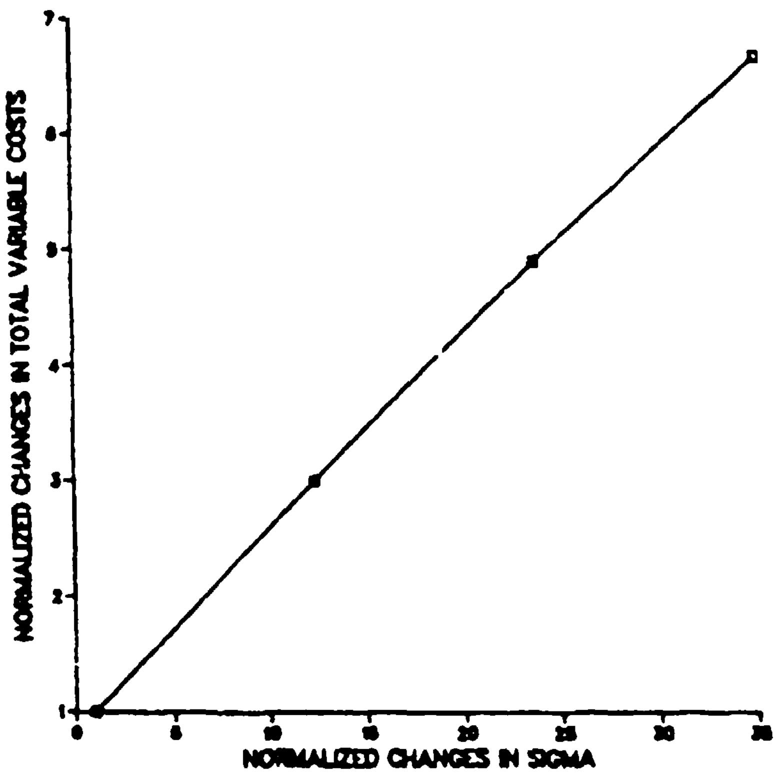

Figure 4. Total Cost Sensitivity to Sigma

These graphs highlight, in a general sense, the theoretical cost effects of variability in leadtime demand. Figure 1 shows that as σ increases over the relevant range the ordering costs developed in the Hadley-Whitin <Q,r> model decay in a nonlinear manner. In contrast, Figures 2 and 3 show the corresponding effects on the holding cost and stockout cost components of the <Q,r> model. There both cost elements increase in a roughly linear fashion over the relevant range with $(\partial BC/\partial\sigma) > k \times (\partial HC/\partial\sigma)$ (where $k \cong 4.5$). The reaction of total variable costs to σ has been included to show the overall effect. It should be remembered that the effects of each of the other three cost elements will be dampened when translated into total variable cost.

This sensitivity analysis indicates that a study of the sources of leadtime demand variance would help reduce holding costs but would also generate particularly beneficial effects on stockout costs. The identification of the causes of demand variance is the subject of the following chapter.

V. HYPOTHESIZED CAUSES OF DEMAND VARIABILITY

Demand randomness results from two sources. There is the truly patternless variation that is unpredictable and uncontrollable, but there is also the variation which results from the way data are collected or reported during a given operational schedule. This second source of variation is the subject of analysis of this chapter.

Erratic items constitute an appreciable portion of the military's inventory population. Silver [Ref. 11] addressed this issue and it is also demonstrated by the coefficients of variation found in the UICP sample data discussed above. Silver maintains that imperfections in the wholesale management information reporting system are a primary cause of erratic demand. (FMSO calls their inventory reporting network the Transaction Item Reporting (TIR) System.)

The TIR system is a tri-level organization which subscribes to a policy of geographical responsibility for supply support. The first level of the TIR's multi-echelon network is the end-user or consumer level (e.g., a shipboard supply department). Level two is composed of several retail outlets such as the at-sea Mobile Logistics Support Force (MLSF) ships and the shore-based stock points (Naval Supply Centers, industrial rework facilities, Naval Air Stations, etc.). The final tier contains the Navy's two wholesale activities--the Inventory Control Points.

Under the most common scenario, a shipboard supply department receives a routine demand request from one of its customer departments. If the demand reduces the ship's available stock past the reorder point or if the demand is for an unsupported item, a replenishment requisition is submitted to the nearest retail outlet by one of two means. For ships operating at sea with an assigned MLSF unit, the replenishment requisition is submitted directly to the MLSF ship. For ships operating without MLSF support or for those which are inport when the demand occurs, the replenishment requisition is deposited with the nearest shore-based retail outlet. Clearly for situations where a customer-ship operates at sea for extended periods without MLSF support, the replenishment requisition encounters substantial delays before reaching the TIR's retail level. Under either case when the requisition ultimately reaches a retail activity, the TIR system activates and provides transaction status to all levels. When the available stock at the retail outlet reaches its reorder point, a collective replenishment requisition is submitted to the ICP. This requisition reflects the current and anticipated future demands from the retail outlet's geographically assigned customers. In this cascading fashion every demand which originates at the consumer level ultimately reaches the wholesale level where the ICP is tasked with the system-wide reorder and budgetary responsibilities.

A simulation was conducted to illustrate how the TIR organizational structure may cause truly non-erratic consumer level demands to be observed as the highly erratic demand actually seen at the ICP level. (See Lewis and Uribe [Ref. 12] and FORTRAN source code, DEMSIM.) The framework for this simulation was adopted from Shields [Ref. 13]. The simulation modified the present TIR demand reporting scheme by inserting an artificial reporting channel which reports all consumer demands directly to the ICP as they occur. To date this reporting medium has been reserved for only high priority requisitions. This alternate reporting channel provides two valuable capabilities. First by directly reporting user-demands, the ICP's records will accurately reflect the demand patterns occurring on the consumer level. Second, the ICP recording operation is expedited by eliminating the reporting delays incurred when ships operate without MLSF services. Together these accuracy and timeliness considerations can have a big impact on the effectiveness of an ICP.

The structure for the DEMSIM program is as follows:

1) assume a 30 ship population with each ship operating independently over an 18 year active service life.
2) initial ship inport and at-sea assignments were randomly selected. (The terms "inport" and "at-sea" are meant only to describe when a retail supply activity is readily available).

3) assume inport periods follow a Uniform [5,30] distribution and at-sea periods follow a Uniform [5,45] distribution.

4) generate demands in a random manner following a compound Poisson process where demand interarrival times are Exponential and demand requisition sizes are Poisson.

5) record demands according to:

   a) the indirect reporting system presently used by ICP.

   b) the artificial system where the ICP receives observations directly from the consumer.

6) aggregate each demand record into quarterly groupings and compute the variance of each time series.

7) repeat the process 50 times.

The result of the simulation supports a similar finding to that of Shields [Ref. 13], that demand variance is substantially reduced using the alternate reporting method. After 50 replications the direct reporting scheme demonstrated an average variance of 3050 as opposed to 5560 for the indirect ICP reporting system (a 45% reduction).

This simulation is meant to highlight only one cause of erratic demand. Presumably other changes in the demand recording system could yield additional improvements. Examples of such changes are:

* Limited Demand History--continued strides in computer technology will make storage of longer demand histories

an economic reality. Greater depth in the demand history would facilitate aggregation by other than a quarterly basis. A change in the base time period could provide a smoother stream of observations.

* Customer Identity--The interaction of large customers (e.g., naval bases) who order more product less often with small customers (e.g., destroyers) who order less product more often might cause high variability. It may prove advisable to monitor a few large customers on an individual basis.
* Customer Buying Habits--A practice of batch ordering could easily be a contributing factor. Actual consumption of material may follow a stable pattern, however, due to such factors as funding and increased operational commitments material is often ordered in large lots.
* Product Identity--The disaggregation of products into their life cycle states (growth, steady state, gradual phase-out) might produce different and distinct demand patterns.

Whether such changes could or even should be implemented largely depends on the results gleaned from comparing the inventory cost savings against the cost of altering the demand recording system. This study does not undertake such a task but focuses instead on a more pertinent issue--the dollar cost of forecast accuracy. That is, for a given demand pattern how desirable is it from an inventory cost perspective to pursue a more accurate forecasting model?

VI. COST IMPACT OF FORECAST ERROR

The final phase of the study uses a computer simulation to examine how forecast error affects ordering, holding and stockout costs. This examination does not suggest how to improve forecasts but it does indicate if it is worth doing anything at all.

The <Q,r> model presented in Chapter IV was a representation of a theoretical inventory cycle for which stationary annual demand rates were applicable. Here the interest is in measuring the actual inventory costs which an ICP incurs when annual demand, due to forecasting inaccuracy, is no longer stationary and when both the reorder quantities (Q_i) and reorder points (r_i) vary for each i^{th} cycle. To conduct such an analysis requires a type of "bookkeeping" computer routine capable of both maintaining the three inventory cost "accounts" and computing Q_i and r_i for each cycle.

For the purposes of this chapter, the i^{th} cycle length (T_i) is defined as the interval of time between receipt of successive orders. Registering cycle order costs reduces to the simple task of posting the cost per order (A) once each cycle. The second account, holding costs, is posted in one of two ways. First, if no backorders occur then the cycle holding costs are $\frac{1}{2}T_i$[(Opening Inventory)$_i$ + (Closing Inventory)$_{i-1}$]. If a backorder does occur, however, the

cycle holding costs are just $\frac{1}{2}[T'_i(\text{Opening Inventory})_i]$ where T'_i is that increment of T_i for which the inventory balance was positive. It should be noted that in exercising this actual inventory cycle the opening cycle inventory may differ from the $Q+(r-\mu)$ quantity found in the theoretical inventory cycle of Chapter IV. A more accurate representation is $nQ_i+(r_i-\mu_i)$ where n is an integer. This is necessary to ensure that the reorder point for each successive cycle will be reached. That is, since Q_i and r_i change with each cycle under certain situations an integer multiple of Q_i must be ordered during the i^{th} cycle to enable the i+1 opening cycle inventory to exceed its reorder point, r_{i+1}.

As to the third account, stockout costs, two possibilities must be considered. The first possibility is that the backorder cost is π per actual backorder with no penalty assigned for the length of time the backorder exists. Second, the actual backorder cost, $\hat{\pi}$, could also be considered as a function of the time the backorder exists $(T_i - T'_i)$. Separate accounts are used to examine the effects of forecast error on each possibility.

Before presenting a summary of the structure of the computer simulation, a measure of forecast error is required to demonstrate the cost effects for various magnitudes of forecast error. The difficulties of dealing with a single criterion of forecast accuracy was addressed earlier. In spite of the fact that it can at times be an unreliable

figure of merit (see Tables 3 and 4), MSE was selected as the measure of accuracy. Specifically, an array of eleven equally spaced values ranging from 0 to 5000 was chosen (i.e., $MSE(k) \in [0,5000]$, $k = 1,11$). This range of values partially reflects the MSE quantities found in Tables 3 and 4.

The simulation computer program (see MSESIM FORTRAN) borrowed the input parameters found in the INVENTOR source code discussed in Chapter IV (with $\sigma = 10$ here). In the MSESIM routine a demand value ($\lambda_i \sim$ NORMAL(180,225)) and a leadtime ($LT_i \sim$ NORMAL(6(mos),1)) were generated for each cycle using an available random number generator (see [Ref. 12]). Using the synthetic demand rate, the available cycle stock level is depleted until the cycle reorder point (r_i) is reached. This triggers the placement of an order of size nQ_i such that this replenishment quantity will exceed r_{i+1}. Stocks continue to deplete at a rate of λ_i over the synthetic leadtime period (LT_i). Upon reaching the end of LT_i the cycle T_i is completed and the reorder quantity nQ_i arrives. At this point the accounts for ordering, holding and stockout costs are updated to reflect the costs actually incurred during the cycle. Next, Q_{i+1}, and r_{i+1} are computed using the basic algorithm found in Chapter IV except that λ_i is deliberately falsified to reflect the forecast error introduced by the chosen forecasting model. (Forecast errors (FE_i) were randomly generated as NORMAL(MSE(k), 1) deviates.) In this way, the FE_i provided by the

forecasting model causes a non-optimal Q_{i+1} and r_{i+1} to be computed. This process continues until a time counter reaches a specified upper limit at which time the evolution is rerun for another pass. After fifty passes the next candidate forecast error (MSE(K+1)) is introduced and the entire simulation process repeats for another set of fifty passes. After all eleven values of MSE(K) are used the computer program plots the grand average for each cost account as a function of its corresponding value of MSE(K) producing the graphs which follow.

The figures presented below are the results of the MSESIM computer routine just described. Again each ordinate axis is normalized to facilitate comparison. Also for completeness both forms of stockout costs (unit and time weighted) and their corresponding total variable cost graphs follow the ordering and holding cost plots.

A review of Figures 5-10 shows that both ordering and holding costs exhibit relatively minor changes over the relevant range (9% decrease; 6% increase, respectively). The roughly linear increases in both stockout costs are quite dramatic especially for time-weighted backorders where greater than a five fold increase is observed. Figures 8 and 10, the two total variable cost graphs, must be viewed with caution for, once again, their behavior is directly influenced by the particular values selected for A, IC, π, σ.

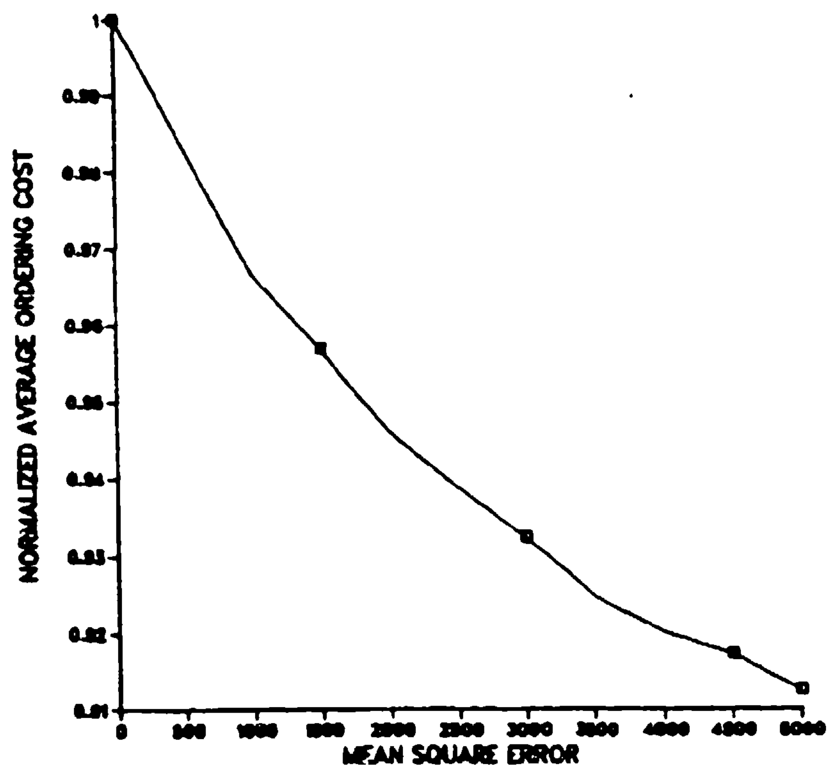

Figure 5. Ordering Cost Sensitivity to MSE

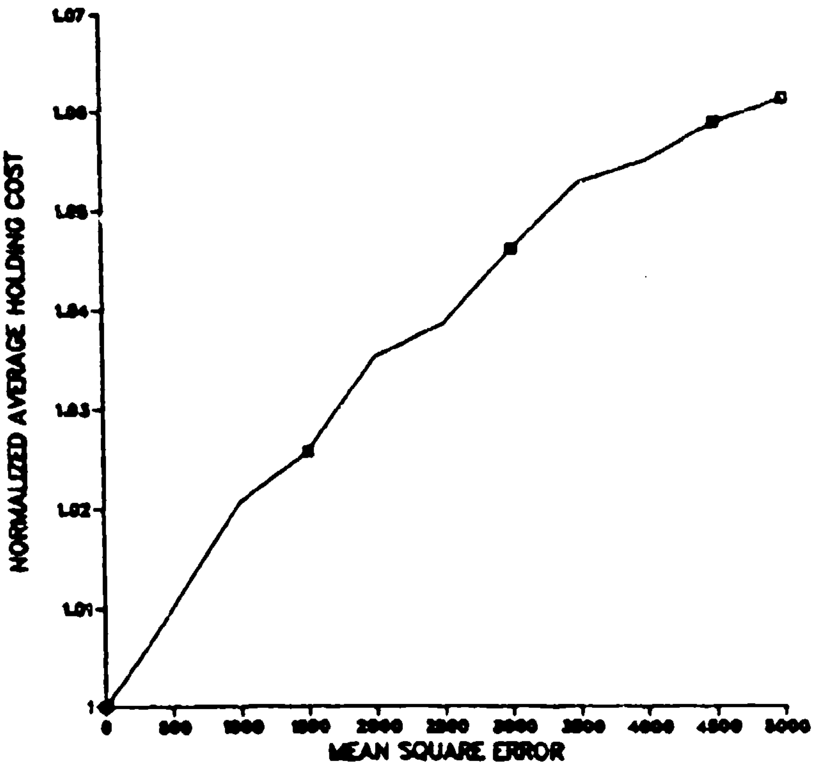

Figure 6. Holding Cost Sensitivity to MSE

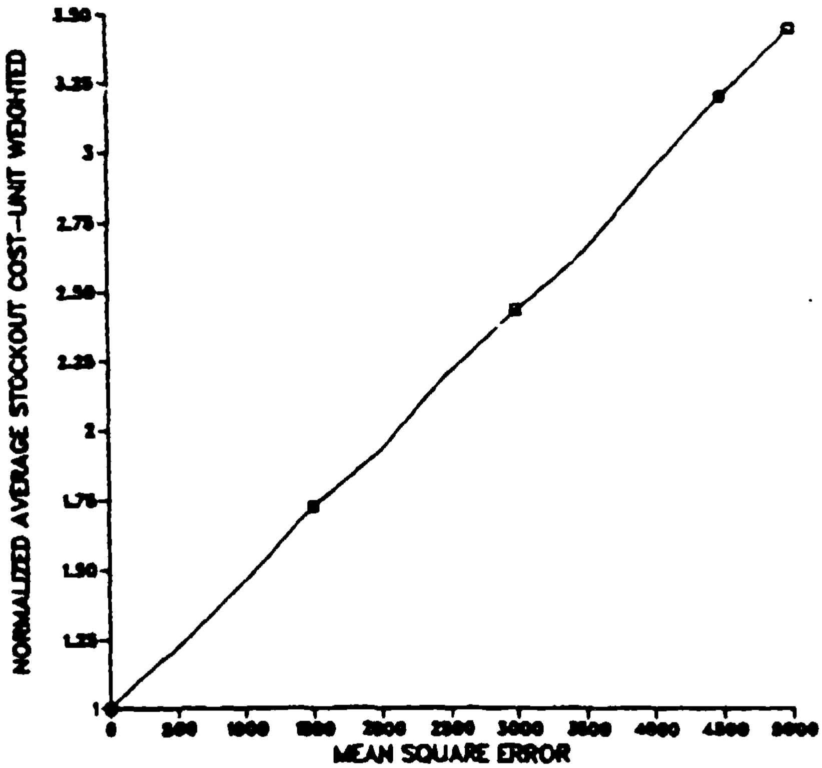

Figure 7. Stockout Cost (Unit Weighted) Sensitivity to MSE

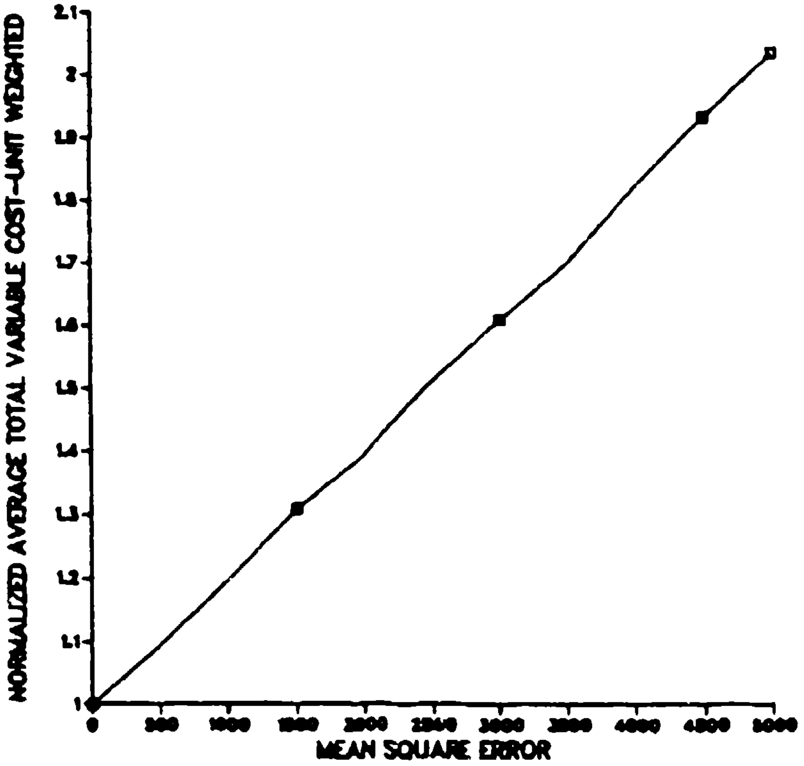

Figure 8. Total Cost (Unit Weighted) Sensitivity to MSE

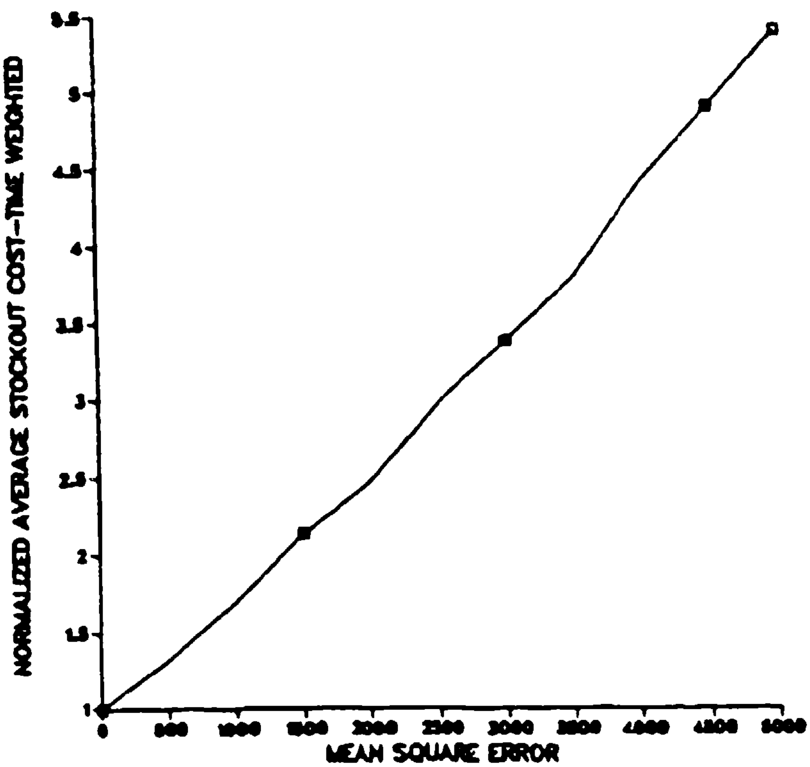

Figure 9. Stockout Cost (Time Weighted) Sensitivity to MSE

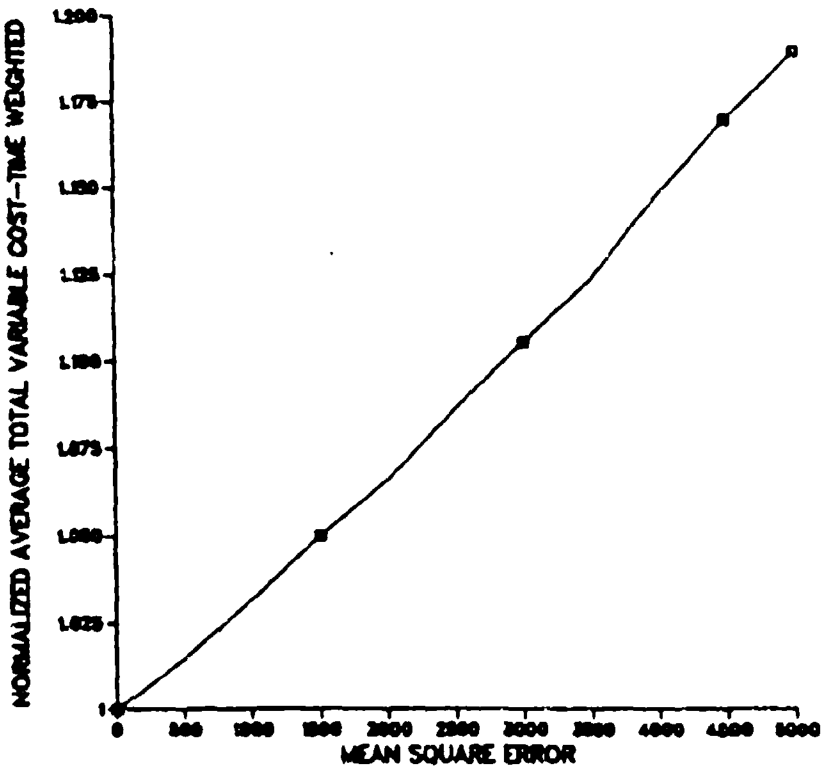

Figure 10. Total Cost (Time Weighted) Sensitivity to MSE

The conclusions gleaned from these graphical displays are two. First, the consequences of even severe forecast error on both ordering and holding costs appear relatively insignificant. The second and more profound finding is that a particular forecasting model's accuracy (as measured by MSE) appears to play a vital role in keeping total stockout costs reasonable.

VII. CONCLUSIONS

A. SUMMARY AND FINDINGS

The study began with a comparison of the SPCC forecasting process to an unrefined form of a newer computer-oriented technique. The use of several effectiveness measures showed neither exponential smoothing nor focus forecasting performed significantly better in forecasting actual SPCC demands. One outgrowth of the comparison was the preponderance of erratic-demand patterns in the ICP inventory population. Next a sensitivity analysis was designed to measure the cost effects of demand variability. This analysis indicated that reductions in demand variability generate generous cost savings, particularly in the form of reduced stockout costs. Not content with viewing the erratic demand situation as inflexible, two research directions were pursued: (1) a change to the demand pattern; (2) the cost effects of changing the forecasting model. First the inclusion of an artificial demand reporting channel produces considerable reductions in demand variance. A second and, presumably, more complicated improvement to the demand forecasting process would be the development of a model capable of accurately forecasting erratic items. To gain insight into the expected economic worth of any such model, the study concluded with an examination of the cost effects

of forecast error. There it was found that stockout costs decrease drastically as forecast accuracy improves.

B. RECOMMENDATIONS FOR FURTHER STUDY

Follow-on research in the areas listed below may augment the research conducted in this study.

1) Conduct further investigation into modifying the TIR reporting system by routing all consumer demands directly to the ICP.
2) Investigate other causes of demand variability and examine the corrective procedures necessary to smooth input demand data. (Several possible sources were hypothesized in Chapter V.)
3) Continue to analyze computer-oriented forecasting techniques. Since the development of the exponential smoothing concept, technological advancements in the computer field have lessened computational and data storage costs. Newer, innovative forecasting methods capitalize on these advancements. Research into dependable forecasting models which are easily understood, easily maintained and easily adapted by a multi-item inventory activity should receive continued sponsorship. The focus forecasting concept is one possible candidate.

APPENDIX A

COMPUTER PROGRAM SOURCE CODE

```
//TWCJOBBB JOB (2885,0281),'N.SULLIVAN',CLASS=C
//*MAIN ORG=NPGVM1.2885P
// EXEC FORTXCLG
//FORT.SYSIN DD *
C***********************************************************************
C***********************************************************************
C**********************    BUCKET FORTRAN    ****************************
C***********************************************************************
C***********************************************************************
C
C      THIS PROGRAM CONVERTS FMSO 5A SIMULATOR DEMAND DATA INTO QUARTERLY
C      "BUCKETS". FOR CONVENIENCE NIIN'S ARE REPLACED BY DUMMY ITEM
C      NUMBERS. PRICE & DEN'S B022& A019 ARE ALSO READ. QUARTERLY DEMANDS
C      ARE PARTITIONED INTO SEPARATE FILES.
C
       INTEGER QTR,DAY(46),AMOUNT(46),D(44),DEMAND,RT(12221),C,OG
       REAL MAD,PRICE,FRCST,PLT,PLTMAD,CC
C
       DATA D/44*C/,ITEM,C,OG,PRICE,FRCST,MAD/0,0,'A',0.0,0.0,0.0/
       DATA RT/12221*0/
C
       LENGTH=12221
       LLNGTH=LENGTH-1
C      READ RECORD TYPE (1 OR 2)
       DO 50 I=1,LENGTH
          READ(5,500,END=88)  RT(I)
50     CONTINUE
88     REWIND 5
       J=1
10     IF(J.GT.LLNGTH) GO TO 20
          IF(RT(J).EQ.1) GO TO 1
4                READ(5,520) (DAY(L),AMOUNT(L),L=1,46)
                 J=J+1
                 DO 5 K=1,46
                      QTR=DAY(K)/91 + 1
                      DEMAND=D(QTR) + AMOUNT(K)
                      D(QTR)=MAXO(0,DEMAND)
5                CONTINUE
                 IF(RT(J).EQ.2) GO TO 4
                 CC=FLOAT(C)
                 IF(AMOD(CC,2.0).GT.0.0) WRITE(8,610) (D(L),L=1,36)
                 IF(AMOD(CC,2.0).EQ.0.0) WRITE(10,610) (D(L),L=1,36)
                 GO TO 10
1         CONTINUE
                 ITEM=ITEM + 1
                 READ(5,510) C,OG,PRICE,PLT,PLTMAD,FRCST,MAD
                 J=J+1
                 CC=FLOAT(C)
```

```
            IF(AMOD(CC,2.0).GT.0.0) WRITE(7,620) ITEM,C,OG,PRICE,PLT,
     *                                   PLTMAD,FRCST,MAD
            IF(AMOD(CC,2.0).EQ.0.0) WRITE(9,620) ITEM,C,OG,PRICE,PLT,
     *                                   PLTMAD,FRCST,MAD
C        RE-INITIALIZE QUARTERLY DEMANDS D(QTR) TO 0
15       DO 16 L=1,44
            D(L)=0
16       CONTINUE
         GO TO 10
20    CONTINUE
      WRITE (6,999) ITEM
      STOP
500   FORMAT(I1)
510   FORMAT(1X,I1,A1,9X,F10.2,39X,F4.2,F3.1,18X,F10.5,F10.5)
520   FORMAT(1X,46(4X,2I4,1X),1X)
610   FORMAT(1X,9I8)
620   FORMAT(1X,I4,2X,I1,A1,5(F10.2,2X))
999   FORMAT(1X,I4)
      END
/*
//GO.FT07F001 DD DISP=SHR,DSN=MSS.S2885.CP
//GO.FT08F001 DD DISP=SHR,DSN=MSS.S2885.CB
//GO.FT09F001 DD DISP=SHR,DSN=MSS.S2885.RP
//GO.FT10F001 DD DISP=SHR,DSN=MSS.S2885.RB
//GO.SYSIN DD DISP=SHR,DSN=MSS.S2885.DEMSPC
//
```

```
C*****************************************************************
C*****************************************************************
C***************************   ESC FORTRAN   *********************
C*****************************************************************
C*****************************************************************
C
C
C      THIS PRCGRAM EXERCISES THE UICP EXPONENTIAL SMOOTHING
C      DEMAND FORECASTING ROUTINE
C
C      DICTIONARY:
C
C      T  TIME INDEX (T=9 WILL BE FIRST PERIOD OF INTEREST)
C                    (T=5-8 ARE USED TO SMOOTH INITIAL VALUES)
C                    (T=1-4 ARE USED TO ESTABLISH SEED VALUES)
C      XSTART  LOWER LIMIT ON TIME INDEX
C      XEND    UPPER LIMIT ON TIME INDEX
C      F(T)    FORECASTED DEMAND FOR PERIOD T
C      D(T)    ACTUAL DEMAND FOR PERIOD T
C      ERROR(T)     D(T)-F(T)
C      MAD     MEAN ABSOLUTE DEVIATION FOR ES MODEL
C      LL      LOWER LIMIT ON DEMAND CONTROL FILTER
C      UL      UPPER LIMIT ON DEMAND CONTROL FILTER
C      TD      TRENDING INDEX USED IN ES MODEL
C      OUTSUM  STEP INCREASE/DECREASE COUNTER
C      KOUNT   COUNTER OF # OF FORECASTS MADE
C      ALPHA   SMOOTHING WEIGHT OF ES MODEL
C      OUTS    # OF OUTLIERS ENCOUNTERED
C      XMSE    MEAN SQUARED ERROR(MSE ARRAY VERSION)
C      MANY    # OF ITEMS IN SAMPLE
C      OUTU    COUNTER ON # OF TIMES UPPER TOLERANCE BOUND IS REACHED
C      OUTL    COUNTER ON # OF TIMES LOWER TOLERANCE BOUND IS REACHED
C      FAVG    STABILIZED QUARTERLY DEMAND RATE( SINCE UICP MODEL USES
C              A STATIONARY RATE)
C      PRICE   ITEM REPLACEMENT PRICE
C      PRWTD   PRICE WEIGHTED FORECAST ERROR
C
C
C
       REAL F(36),D(36),ERROR(18500),PRWTD(18500),XMSE,PRICE,SUM
       REAL CD(18500),CF(18500),MAD,MSE(18500)
C
       INTEGER OUTSUM,OUTS,T,TT,XEND,XSTART,MANY,ITEM,KOUNT,OUTU,OUTL
C
C
       DATA F/36*0.0/,D/36*0.0/
       DO 88 XSTART=13,25,4
       OUTS=0
```

```
      KOUNT=0
      XMSE=0.0
      MANY=4530
      XEND=XSTART+3
      DO 150 ITEM=1,MANY
         OUTSUM=0
         OUTU=0
         OUTL=0
         READ(1,500) (D(L),L=1,36)
         READ(2,501) PRICE
C     ESTABLISH INITIAL FORECAST & MAD USING YEAR #1
         F(5)=(D(1)+D(2)+D(3)+D(4))/4.0
         MAD=(ABS(D(1)-F(5))+ABS(D(2)-F(5))+ABS(D(3)-F(5))+ABS(D(4)-F(5)
     *   ))/4.0
         F(4)=F(5)
C
C     USE YEARS #2 & #3 TO STABILIZE FORECASTS
C     YEARS #4 - #7 WILL BE USED FOR EVALUATING FORECASTS
C     YEARS #8 - #9 ARE HELD IN TEMPORARY RESERVE FOR LATER COMPARISONS
C
         DO 140 T=6,XEND
            TT=T-(XSTART-1)
            ALPHA=.1
C     TREND TEST
            SUM=D(T-1)+D(T-2)+D(T-3)+D(T-4)
            IF(SUM.EQ.0.0) GO TO 99
            TD=(2.0*(D(T-1)+D(T-2)))/(D(T-1)+D(T-2)+D(T-3)+D(T-4))
            IF(((TD.GT.1.1).AND.((D(T-2).GE.F(T-2)).AND.(D(T-1).GE.
     *      F(T-1)))).OR.((TD.LT..9).AND.((D(T-2).LE.F(T-2)).AND.
     *      (D(T-1).LE.F(T-1))))) ALPHA=.3
C
C     DESIGNATE MARK CODES
99          IF(D(T-1).GT.5.0) GO TO 10
C     MARK 0,1,3 CATEGORIES
C     CONDUCT DEMAND FILTER CHECKS
            UL=AMAX1((6.0*F(T-1)),2.0)
            IF(D(T-1).LE.UL) GO TO 20
C     OUT OF CONTROL CONDITION
                  OUTS=OUTS+1
                  ALPHA=0.0
                  F(T)=F(T-1)
                  MAD=.1*ABS(D(T-1)-F(T-1))+.9*MAD
C     STEP INCREASE/DECREASE CHECK
                  OUTSUM=OUTSUM+1
                  IF(OUTSUM.LT.2) GO TO 30
                     OUTSUM=0
                     F(T)=(D(T-1)+D(T-2))/2.0
                     GO TO 30
```

```
C       IN CONTFCL CONDITION
20              CONTINUE
                        OUTSUM=0
                        F(T)=ALPHA*D(T-1)+(1.0-ALPHA)*F(T-1)
                        MAD=.1*ABS(D(T-1)-F(T-1))+.9*MAD
                        GO TO 30
C       MARK 2.4  CATEGORIES
10              CONTINUE
C       FILTER CHECKS
                UL=7.5*MAD+F(T-1)
                LL=AMAX1((7.5*MAD-F(T-1)),0.0)
                IF((D(T-1).GE.LL).AND.(D(T-1).LE.UL)) GO TO 40
C       OUT OF CONTFOL
                OUTS=OUTS+1
                ALPHA=0.0
                F(T)=F(T-1)
                MAD=.1*ABS(D(T-1)-F(T-1))+.9*MAD
C       STEP INCREASES/DECREASES
                IF(C(T-1).GT.UL) OUTU=OUTU+1
                IF(C(T-1).LT.LL) OUTL=OUTL+1
                IF((OUTU.LT.2).AND.(OUTL.LT.2)) GO TO 30
                        IF(OUTU.GE.2) OUTU=0
                        IF(OUTL.GE.2) OUTL=0
                        F(T)=(D(T-1)+D(T-2))/2.0
                        MAD=1.386*F(T)**.746
                        GO TO 30
C       IN CONTROL
40              CONTINUE
                CUTL=0
                GUTL=0
                F(T)=ALPHA*D(T-1)+(1.0-ALPHA)*F(T-1)
                MAD=.1*ABS(D(T-1)-F(T-1))+.9*MAD
30          CONTINUE
            IF(T.LT.XSTART) GO TO 140
                FAVG=(D(T)+D(T+1)+D(T+2)+D(T+3))/4.0
                KOUNT=KOUNT+1
                ERRCR(KCUNT)=FAVG-F(T)
                CD(KOUNT)=FAVG
                CF(KOUNT)=F(T)
                XMSE=XMSE+ERROR(KOUNT)**2
                MSE(KOUNT)=ERROR(KOUNT)**2
                PRWTD(KOUNT)=PRICE*ERROR(KOUNT)
140         CONTINUE
150     CONTINUE
        REWIND 1
        REWIND 2
        IYEAR=XEND/4
        XMSE=XMSE/FLOAT(KOUNT)
```

```
      CALL CORLAT(CD,CF,KOUNT,R)
      WRITE(3,601) XMSE,OUTS,R
      CALL HISTGP(MSE,KOUNT,0)
      CALL HISTGP(ERROR,KOUNT,0)
      WRITE(6,600) IYEAR
      WRITE(6,604) XMSE,OUTS,R
      CALL HISTGP(PRWTD,KOUNT,0)
      WRITE(6,602) IYEAR
      WRITE(6,604) XMSE,OUTS,R
88    CONTINUE
      STOP
500   FORMAT(1X,9F8.0)
501   FORMAT(9X,F10.2)
600   FORMAT(//,' CONSUMABLE(ES) PLOT UNPRICED ERRORS FOR YEAR ',I5)
602   FORMAT(//,' CONSUMABLE(ES) PLOT PRICED ERRORS FOR YEAR ',I5)
604   FORMAT(' MSE = ',F10.2,' #OUTLIERS = ',I10,' CORRELATION =',F10.2)
601   FORMAT(F10.2,I10,F10.2)
      END
C
C     THIS SUBROUTINE CALCULATES THE PEARSON'S CORRELATION COEFFICIENT
      SUBROUTINE CORLAT(CD,CF,KOUNT,R)
      REAL CD(18500),CF(18500)
      R=999.9
      CDSUM=0.0
      CFSUM=0.0
      TOP=0.0
      DL=0.0
      DR=0.0
      DO 700 JJ=1,KOUNT
         CDSUM=CDSUM+CD(JJ)
         CFSUM=CFSUM+CF(JJ)
700   CONTINUE
      CDBAR=CDSUM/FLOAT(KOUNT)
      CFBAR=CFSUM/FLOAT(KOUNT)
      DO 701 JJ=1,KOUNT
         TOP=TOP+(CD(JJ)-CDBAR)*(CF(JJ)-CFBAR)
         DL=DL+(CD(JJ)-CDBAR)**2
         DR=DR+(CF(JJ)-CFBAR)**2
701   CONTINUE
      BOTTOM=SQRT(DL*DR)
      IF(BOTTOM.EQ.0.0) GO TO 702
         R=TOP/BOTTOM
702   RETURN
      END
```

```
C*******************************************************************
C*******************************************************************
C******************************   FOCUS FORTRAN   ******************
C*******************************************************************
C*******************************************************************
C
C
C      THIS PROGRAM EXERCISES A SIMPLIFIED VERSION OF B.T. SMITH'S
C      FOCUS FORECASTING MODEL
C
C
C      DICTIONARY:
C
C      T          TIME INDEX T=9 EQUIVALENT TO 9TH QUARTER,ETC.
C      XSTART     LOWER LIMIT ON TIME INDEX
C      XEND       UPPER LIMIT ON TIME INDEX
C      D(J)       INPUT STREAM OF HISTORICAL DEMANDS
C      STRAT      ARRAY CONTAINING FORECASTS FOR T-1; MENU CONTAINS 6
C                 DIFFERENT STRATEGIES.
C      CHOICE     BEST STRATEGY SELECTED FOR FORECASTING PERIOD T
C      DIFF       DIFFERENCE IN FORECAST & ACTUAL DEMAND FOR T-1
C      BDIFF      BEST DIFFERENCE IN FORECAST & ACTUAL DEMAND FOR T-1
C      FRCST      FORECASTED DEMAND FOR PERIOD T
C      KOUNTX     COUNT OF # OF TIMES STRATEGY X HAS BEEN SELECTED
C      MSE        MEAN SUUARED ERROR
C      FAVG       THE STABILIZED QUARTERLY DEMAND RATE (SAME AS THAT USED
C                 IN LICP ES MODEL
C      PRICE      ITEM REPLACEMENT PRICE
C      PRWTD      PRICE WEIGHTED FORECAST ERROR
C
C
       REAL       D(36),STRAT(10),PRICE,XMSE,PRWTD(18500),ERROR(18500),
     *            CD(18500),CF(18500),MSE(18500)
C
       INTEGER T,CHOICE,XSTART,XEND
C
C
       DATA       KOUNT1,KOUNT2,KOUNT3,KOUNT4,KOUNT5,KOUNT6/6*0/
C
C
       MANY=522
       DO 88 XSTART=13,25,4
          XEND=XSTART+3
          XMSE=0.0
          KOUNT=0
          KOUNT1=0
          KOUNT2=0
          KOUNT3=0
```

```
      KOUNT4=0
      KOUNT5=0
      DO 150 I=1,MANY
         READ(1,500) (D(L),L=1,36)
         READ(2,501) PRICE
         DO 140 T=XSTART,XEND
C
C              STRATEGY # 1 - LAST PERIOD THIS YEAR
               STRAT(1)=D(T-2)
C
C              STRATEGY # 2 - THIS PERIOD LAST YEAR
               STRAT(2)=D(T-5)
C
C              STRATEGY # 3 - TWO PERIOD MOVING AVERAGE
               STRAT(3)=.5*(D(T-2)+D(T-3))
C
C              STRATEGY # 4 - FOUR PERIOD MOVING AVERAGE
               STRAT(4)= .5*STRAT(3)+.25*(D(T-4)+D(T-5))
C
C              STRATEGY # 5 - FULL PERIOD MOVING AVERAGE
               STRAT(5)=.5714*STRAT(4)+.14285*(D(T-6)+D(T-7)+D(T-8))
C
C              STRATEGY # 6 - COMBINED FORECAST
               STRAT(6)=.2*(STRAT(1)+STRAT(2)+STRAT(3)+STRAT(4)+
     *                  STRAT(5))
C
C           SELECT STRATEGY WHICH BEST FORECASTS PERIOD T-1
               CHOICE=1
               BDIFF=ABS(D(T-1)-STRAT(1))
               DO 110 K=2,6
                  DIFF=ABS(D(T-1)-STRAT(K))
                  IF(DIFF.GE.BDIFF) GO TO 110
                     BDIFF=DIFF
                     CHOICE=K
110            CONTINUE
C
C           APPLY SELECTED STRATEGY IN FORECASTING PERIOD T
               GO TO (1,2,3,4,5,6),CHOICE
1              CONTINUE
                  FRCST=D(T-1)
                  KOUNT1=KOUNT1+1
                  GO TO 130
2              CONTINUE
                  FRCST=.5*(D(T-4)+D(T-8))
                  KOUNT2=KOUNT2+1
                  GO TO 130
3              CONTINUE
                  FRCST=.5*(D(T-1)+D(T-2))
```

```
                KOUNT3=KOUNT3+1
                GO TO 130
4           CONTINUE
                FRCST=.25*(D(T-4)+D(T-3)+Q(T-2)+D(T-1))
                KOUNT4=KOUNT4+1
                GO TO 130
5           CONTINUE
                FRCST=.875*STRAT(5)+.125*C(T-1)
                KOUNT5=KOUNT5+1
                GO TO 130
6           CONTINUE
                FRCST=.2*(D(T-1)+.5*(D(T-4)+D(T-8))+
     *                   .5*(D(T-1)+D(T-2))+
     *                   .25*(D(T-4)+D(T-3)+D(T-2)+D(T-1))+
     *                   .875*STRAT(5)+.125*D(T-1))
                KOUNT6=KCUNT6+1
130         CONTINUE
            KOUNT=KOUNT+1
            FAVG=(D(T)+D(T+1)+D(T+2)+D(T+3))/4.0
            CD(KOUNT)=FAVG
            CF(KOUNT)=FRCST
            ERROR(KOUNT)=FAVG-FRCST
            XMSE=XMSE+ERROR(KOUNT)**2
            MSE(KOUNT)=ERROR(KOUNT)**2
            PRWTD(KOUNT)=PRICE*ERROR(KOUNT)
140       CCNTINUE
150   CONTINUE
      REWIND 1
      REWIND 2
      IYEAR=XEND/4
      XMSE=XMSE/FLOAT(KOUNT)
      CALL CORLAT(CD,CF,KOUNT,R)
      WRITE(3,601) XMSE,R
      WRITE(3,602) KOUNT1,KOUNT2,KOUNT3,KCUNT4,KOUNT5,KOUNT6
      WRITE(3,602) KOUNT
      CALL HISTGP(MSE,KOUNT,0)
      CALL HISIGP(ERRCR,KOUNT,0)
      WRITE(6,600) IYEAR
      WRITE(6,604) XMSE,R
      CALL HISTGP(PRWTD,KOUNT,0)
      WRITE(6,603) IYEAR
      WRITE(6,604) XMSE,R
88    CONTINUE
      STOP
500   FORMAT(1X,9F8.0)
501   FORMAT(9X,F10.2)
600   FORMAT(//,' REPAIRABLES(FF) PLOT OF UNPRICED ERRORS FOR YEAR',I5)
604   FORMAT(' MSE= ',F10.2,' CORRELATION =',F10.2)
```

```
603   FORMAT(//,' REPAIRABLES(FF) PLOT OF PRICED ERRORS FOR YEAR',I5)
601   FORMAT(F10.2,F10.2)
602   FORMAT(6I10)
      END
      SUBROUTINE CORLAT(CD,CF,KOUNT,R)
      REAL CD(18500),CF(18500)
      R=999.9
      CDSUM=0.0
      CFSUM=0.0
      TOP=0.0
      DL=0.0
      DR=0.0
      DO 700 JJ=1,KOUNT
         CDSUM=CDSUM+CD(JJ)
         CFSUM=CFSUM+CF(JJ)
700   CONTINUE
      CDBAR=CDSUM/FLOAT(KOUNT)
      CFBAR=CFSUM/FLOAT(KOUNT)
      DO 701 JJ=1,KOUNT
         TOP=TOP+(CD(JJ)-CDBAR)*(CF(JJ)-CFBAR)
         DL=DL+(CD(JJ)-CDBAR)**2
         DR=DR+(CF(JJ)-CFBAR)**2
701   CONTINUE
      BOTTOM=SQRT(DL*DR)
      IF(BOTTOM.EQ.0.0) GO TO 702
         R=TOP/BOTTOM
702   RETURN
      END
```

```
C***************************************************************************
C***************************************************************************
C******************************   INVENTOR FORTRAN   ***********************
C***************************************************************************
C***************************************************************************
C
C     THIS PROGRAM RUNS A SENSITIVITY ANALYSIS OF THE THREE ELEMENTS OF
C     TOTAL VARIABLE COST TO CHANGES IN THE VARIANCE PARAMETER OF
C     THE LEAD TIME DISTRIBUTION.
C
C
C
C     DICTIONARY:
C
C     SIG      THE STANDARD DEVIATION PARAMETER FOR LEADTIME DEMAND
C              DISTRIBUTION ( HERE ASSUMED NORMAL(XMU,SIG**2) )
C     MANY     # OF INCREMENTS OF SIG
C     DELTA    LENGTH OF EACH INCREMENT OF SIG
C     LAMDA    ANNUALIZED DEMAND RATE
C     C        ITEM REPLACEMENT PRICE
C     I        HOLDING COST RATE
C     PI       ITEM BACKORDER COST
C     XMU      THE MEAN PARAMETER FOR THE LEADTIME DEMAND DISTRIBUTION
C     QW       WILSON EOQ
C     CHECK    SUBROUTINE WHICH CHECKS FOR UNIQUE SOLUTION FOR Q & R
C     NORM     SUBROUTINE WHICH EXECUTES ITERATIVE SOLUTION ALGORITHM
C              TO APPROXIMATE A OPTIMAL SOLUTION TO Q & R
C     COST     BOOKKEEPING SUBROUTINE WHICH MAINTAINS THE THREE TVC COST
C              ACCOUNTS
C     AOC      ARRAY WHICH STORES OC - ORDERING COSTS
C     AHC      ARRAY WHICH STORES HC - HOLDING COSTS
C     ABC      ARRAY WHICH STORES BC - BACKORDER COSTS
C     ATVC     ARRAY WHICH STORES TVC- TOTAL VARIABLE COSTS
C     ASIG     ARRAY WHICH STORES SIG
C     AOC      ARRAY WHICH STORES OC - ORDERING COSTS
C
C
      REAL     LAMDA,I,PI,OC,HC,QQ(100),Q,AQ(2100),AR(2100),AOC(2100),
     *         AHC(2100),ABC(2100),ATVC(2100),ASIG(2100),AETA(2100),
     *         AZ(2100)
      INTEGER MANY,FLAG
      MANY=1000
      DELTA=.34
      LAMDA=180.0
      C=150.0
      I=.1
      A=500.0
      PI=500.0
      XMU=90.0
```

```
      SIG=10.0
      DO 203 JJ=1,MANY
      QW=SQRT((2.0*LAMDA*A)/(I*C))
      CALL CHECK (LAMDA,A,I,C,PI,XMU,QW,QO,FLAG)
      IF(FLAG.EQ.1)GO TO 201
      CALL NORM(LAMDA,A,C,I,PI,QW,XMU,SIG,Q,R,Z,ETA)
      CALL COST(LAMDA,A,C,I,PI,SIG,Q,R,Z,ETA,TVC,OC,HC,BC)
      GO TO 202
201   Q=QO
      R=0.0
      TVC=0.0
      HC=0.0
      BC=0.0
      Z=0.0
      ETA=0.0
202   AOC(JJ)=OC
      AHC(JJ)=HC
      ABC(JJ)=BC
      ATVC(JJ)=TVC
      ASIG(JJ)=SIG
      SIG=SIG + DELTA
203   CONTINUE
      DENOC=AOC(1)
      DENHC=AHC(1)
      DENBC=ABC(1)
      DENTC=ATVC(1)
      DENSIG=ASIG(1)
      DO 204 K=1,MANY
         AOC(K)=AOC(K)/DENOC
         AHC(K)=AHC(K)/DENHC
         ABC(K)=ABC(K)/DENBC
         ATVC(K)=ATVC(K)/DENTC
         ASIG(K)=ASIG(K)/DENSIG
204   CONTINUE
      CALL TEK618
      CALL PLOTD(ASIG,AOC,MANY,.TRUE.,'LINLIN','SIG SENSITIVITY$',
     *          'SENSITIVITY TO SIGMA$','NORMALIZED CHANGES IN SIGMA$',
     *          'NORMALIZED CHANGES IN ORDERING COSTS$')
      CALL PLOTD(ASIG,AHC,MANY,.TRUE.,'LINLIN','SIG SENSITIVITY$',
     *          'SENSITIVITY TO SIGMA$','NORMALIZED CHANGES IN SIGMA$',
     *          'NORMALIZED CHANGES IN HOLDING COSTS$')
      CALL PLOTD(ASIG,ABC,MANY,.TRUE.,'LINLIN','SIG SENSITIVITY$',
     *          'SENSITIVITY TO SIGMA$','NORMALIZED CHANGES IN SIGMA$',
     *          'NORMALIZED CHANGES IN STOCKOUT COSTS$')
      CALL PLOTD(ASIG,ATVC,MANY,.TRUE.,'LINLIN','SIG SENSITIVITY$',
     *          'SENSITIVITY TO SIGMA$','NORMALIZED CHANGES IN SIGMA$',
     *          'NORMALIZED CHANGES IN TOTAL VARIABLE COSTS$')
      CALL DONEPL
```

```
      STOP
      END
C*****************************************************************************
      SUBROUTINE NORM(XL,A,C,XI,PI,QW,XM,S,Q,R,Z,ETA)
      DIMENSION QQ(100)
      REAL P/3.141593/
      PHI(X)=XK*EXP(-.5*X*X)
      XK=1./SQRT(2.*P)
      QQ(1)=QW
      I=2
10    XH=QQ(I-1)*XI*C/(PI*XL)
      XX=1.-XH
      CALL MDNRIS(XX,Z,IER)
      IF(IER.EQ.129)RETURN
      ORD=PHI(Z)
      ETA=ORD-Z*XH
      QQ(I)=SQRT((2.*XL*(A+(PI*S*ETA)))/(XI*C))
      DIF=ABS(QQ(I)-QQ(I-1))
      IF(DIF.LE.0.001)GO TO 20
      IF(I.EQ.100)GO TO 20
      I=I+1
      GO TO 10
20    Q=QQ(I)
      R=XM+S*Z
      RETURN
      END
C*****************************************************************************
      SUBROUTINE CHECK(XL,A,XI,C,PI,XMU,QW,Q,FLAG)
      XX=(PI*XL)/(XI*C)
      Q=SQRT(2.*XL*(A+(PI*XMU))/(XI*C))
      IF(Q.GE.XX)GO TO 10
      FLAG=0
      RETURN
10    IF(QW.LE.XX)GO TO 20
      FLAG=1
      RETURN
20    CONTINUE
      FLAG=0
      RETURN
      END
C*****************************************************************************
      SUBROUTINE COST(LAMDA,A,C,I,PI,SIG,Q,R,Z,ETA,TVC,OC,HC,BC)
      REAL LAMDA,A,C,I,PI,SIG,Q,R,Z,ETA,TVC,OC,HC,BC
      TVC=-99.99
      OC=-99.99
      HC=-99.99
      BC=-99.99
      IF(Q.LE.0.0) RETURN
```

```
OC=(A*LAMDA)/Q
HC=I*C*((.5*Q)+SIG*Z)
BC=(PI*LAMDA*SIG*ETA)/C
TVC=OC+HC+BC
RETURN
END
```

```
C*****************************************************************
C*****************************************************************
C*****************************   DEMSIM FORTRAN   ****************
C*****************************************************************
C*****************************************************************
C
C
C           THIS PROGRAM SIMULATES THE GENERATION OF DEMANDS BY A COMPOUND
C           POISSON PROCESS. DEMANDS ARE RECORDED BY TWO METHODS: (1) ACCUR
C           ING TO THE PRESENT INDIRECT TIR SYSTEM; (2) ACCORDING TO AN
C           MODIFIED DIRECT METHOD
C
C
C           DICTIONARY:
C
C       REPEAT   # OF REPETITIONS OF THE SIMULATION
C       YEARS    UPPER LIMIT ON TIME COUNTER EXPRESSED IN YEARS
C       IQTRS    UPPER LIMIT ON TIME COUNTER EXPRESSED IN QUARTERS
C       IDAYS    UPPER LIMIT ON TIME COUNTER EXPRESSED IN DAYS
C       SHIPS    # OF SHIPS IN FLEET
C       IX       SEED VALUE FOR RANDOM NUMBER GENERATOR (RNG)
C       DEMICP   ARRAY OF DEMANDS AS SEEN BY ICP UNDER MODIFIED SYSTEM
C       DEMSP    ARRAY OF DEMANDS AS SEEN BY ICP UNDER PRESENT TIR SYSTEM
C       SPHOLD   SUSPENSE FILE OF DEMANDS WAITING TO BE SEEN BY A RETAIL
C                TIR ACTIVITY
C       DAY      PRESENT DATE ON 18 YEAR TIME LINE
C       QTR      PRESENT QUARTER ON 18 YEAR TIME LINE
C       LRND,LEXP,LPOIS   RNG'S (SEE REF 12)
C       COEFFV   SUBROUTINE TO COMPUTE VARIANCE IN DEMICP & DEMSP
C
C
        REAL DATE(10),DEMARR(10),DEMSIZ(10),LAMDA,PAR(10)
C
        INTEGER   YEARS,SHIPS,REPEAT,DEMICP(75),DEMSP(75),
       *          SPHOLD,QTR,INPORT,ATSEA,DETACH,DARRIV,DAY
C
C
        REPEAT=50
        YEARS=18
        IQTRS=YEARS*4
        IDAY=364*YEARS
        SHIPS=30
        IX=55772482
C       REPEAT SIMULATION
        DO 100 J=1,REPEAT
C       INITIALIZE ARRAYS FOR PRESENT RUN
           DO 10 I=1,IQTRS
                DEMICP(I)=0
```

```
            DEMSP(I)=0
10      CONTINUE
        SPHOLD=0
        DO 20 K=1,SHIPS
            DAY=0
C           GENERATE PARAMETERS FOR INTERARRIVAL DISTRIBUTION (EXP)
C           & REQUISITION SIZE DISTRIBUTION (POISSON).
            CALL LRND(IX,PAR,2,1,0)
1           QTR=DAY/91 +1
            DEMSP(QTR)=DEMSP(QTR)+SPHOLD
            SPHOLD=0
C           GENERATE ARRIVAL & DEPARTURE DATES. INPORT PERIOD WILL BE
C           UNIFORM (5,30); ATSEA PERIOD WILL BE DISTRIBUTED UNIFORM
C           (5,45).
C
            CALL LRND(IX,DATE,2,1,0)
            INPORT=INT(100.0*DATE(1)/4.0)+5
            DAY=DAY+INPORT
            IF(DAY.GE.IDAY) GO TO 20
            ATSEA=INT(100.0*DATE(2)/2.5)+5
            DETACH=DAY+ATSEA
C           GENERATE DEMAND ARRIVAL DATE
2           CALL LEXPN(IX,DEMARR,1,1,0)
            DARRIV=INT(7.0*PAR(1)*DEMARR(1))
            IF(DARRIV.GT.ATSEA) GO TO 1
            IF(DARRIV.LT.1) DARRIV=1
            DAY=DAY+DARRIV
            IF(DAY.GE.IDAY) GO TO 20
            IF(DAY.GE.DETACH) GO TO 1
C           GENERATE REQUISITION SIZE
            LAMDA=2.0*PAR(2)
            CALL LPOIS(IX,DEMSIZ,1,1,0,LAMDA)
            QTR=DAY/91 +1
            DEMICP(QTR)=DEMICP(QTR)+MAX1(1.0,DEMSIZ(1))
            SPHOLD=SPHOLD+MAX1(1.0,DEMSIZ(1))
            ATSEA=ATSEA-DARRIV
C           GENERATE NEXT DEMAND
            GO TO 2
20      CONTINUE
        WRITE(2,601)
        CALL COEFFV(YEARS,DEMICP,DEMSP,SMRA,SMRB)
        WRITE(3,602) SMRA,SMRB
        WRITE(2,600) (DEMICP(L),L=1,IQTRS)
        WRITE(2,603)
        WRITE(2,600) (DEMSP(L),L=1,IQTRS)
100     CONTINUE
        STOP
600     FORMAT(1X,8I9)
```

```
601   FORMAT(1X,/,' DEMANDS REPORTED DIRECTLY TO ICP ARE: ')
603   FORMAT(1X,/,' DEMANDS REPORTED INDIRECTLY TC ICP ARE: ')
602   FORMAT(1X,4F15.2)
      END
      SUBROUTINE COEFFV(YEARS,DEMICP,DEMSP,VARB1,VARB2)
      INTEGER DEMICP(200),DEMSP(200),YEARS
      IQTRS=4*YEARS
      MIQTR=4*(YEARS-8)+1
      SUMA1=0.0
      SUMA2=0.0
         DO 200 M=MIQTR,IQTRS
              SUMA1=SUMA1+FLOAT(DEMICP(M))
              SUMA2=SUMA2+FLOAT(DEMSP(M))
200      CONTINUE
      AVGA1=SUMA1/FLOAT(32)
      AVGA2=SUMA2/FLOAT(32)
      SUMB1=0.0
      SUMB2=0.0
         DO 300 M=MIQTR,IQTRS
              SUMB1=SUMB1+(FLOAT(DEMICP(M))-AVGA1)**2
              SUMB2=SUMB2+(FLOAT(DEMSP(M))-AVGA2)**2
300      CONTINUE
      VARB1=SUMB1/FLOAT(31)
      VARB2=SUMB2/FLOAT(31)
      SDA=SQRT(VARB1)
      SDB=SQRT(VARB2)
      SMRA=SDA/AVGA1
      SMRB=SDB/AVGA2
      RETURN
      END
```

```
C*****************************************************************
C*****************************************************************
C*****************************  MSESIM FORTRAN  ******************
C*****************************************************************
C*****************************************************************
C
C
C     THIS PROGRAM COMPUTES AND STORES THE VALUES OF ORDERING,
C     HOLDING, STOCKOUT AND TOTAL VARIABLE COSTS FOR EACH CYCLE
C     WHICH IS ALLOWED TO VARY RANDOMLY OVER TIME.
C
C
C
C     DICTIONARY:
C
C     C       ITEM REPLACEMENT PRICE
C     I       HOLDING COST RATE
C     A       ORDERING COST
C     PI      ITEM STOCKOUT COST
C     T       POSITION ON TIME LINE
C     TIME    UPPER LIMIT OF T
C     REPEAT  # OF REPLICATIONS
C     IX      SEED VALUE FOR RANDOM NUMBER GENERATOR (RNG)
C     MSE     ARRAY OF TEST VALUES FOR MEAN SQUARE ERROR
C     DELTAS  NUMBER OF ELEMENTS STORED IN MSE
C     XINC    SPACING BETWEEN EACH MSE ELEMENT
C     XMU     PARAMETER VALUE FOR MEAN LEADTIME DEMAND
C     SIG     PARAMETER VALUE FOR LEADTIME DEMAND STANDARD DEVIATION
C             (HERE ASSUMED TO BE NORMAL(XMU,SIG**2)
C     LNORM   RNG FOR NORMAL DEVIATES (REF(12))
C     ALAMDA  ANNUAL DEMAND RATE (HERE-NORMAL(180,15**2)
C     LT      LENGTH OF LEADTIME
C     SUMOC   TOTAL OF OC - ORDERING COSTS
C     SUMHC   TOTAL OF HC - HOLDING COSTS
C     SUMBC   TOTAL OF BC - BACKORDER COSTS (UNIT WEIGHTED)
C     SUMBCT  TOTAL OF BCT- BACKORDER COSTS (TIME WEIGHTED)
C     KOUNT   ARRAY INDEX
C     T1      LENGTH OF CYCLE TIME UNTIL REORDER POINT IS REACHED
C     T2      LENGTH OF CYCLE TIME FOR WHICH BACKORDER OCCURRED
C     NI      INVENTORY BALANCE
C     TEMPNI  TEMPORARY COPY OF NI
C     R       REORDER POINT
C     Q       REORDER QUANTITY
C     DEVIAT  UNBIASED ERROR FACTOR
C     INVENT  SUBROUTINE VERSION OF INVENTOR FORTRAN PROGRAM
C
      REAL C,I,A,PI,TIME,XINC,ALAMDA(5000),LT(5000),SIG,
     *     MSE(100),SUMOC,SUMHC,SUMBC,SUMBCT,T,Q,R,TEMPQ,
     *     NI,DEVIAT(5000),T1,T2,TEMPNI,XMU,OC,HC,BC,BCT,SIGN,LAMDA,
```

```
     *     AOC(100),AHC(100),ABC(100),ABCT(100),ATVC(100),ATVCT(100)
C
      INTEGER REPEAT,IX,DELTAS,KOUNT,MULT
C
      C=150.0
      I=.10
      A=500.0
      PI=500.C
      TIME=1000.0
      REPEAT=50
      IX=55772482
      DELTAS=11
      XINC=500.0
      SIG=10.0
C
C     OBTAIN ANNUAL DEMAND RATES; LEADTIMES; ANNUAL DEMAND RATE VARIANCE
C     & ANNUAL LEADTIME DEMAND VARIANCE
      CALL LNCRM(IX,ALAMDA,5000,1,0)
      CALL LNCRM(IX,LT,5000,1,0)
      DO 1 N=1,5000
         ALAMCA(N)=AMAX1(5.0,(15.0*ALAMDA(N)+ 180.0))
         LT(N)=(AMAX1(1.5,(1.0*LT(N)+6.0)))/12.0
1     CONTINUE
      DO 2 K=1,DELTAS
         MSE(K)=XINC*FLOAT(K-1)
2     CONTINUE
      DO 100 K=1,CELTAS
         SUMOC=0.C
         SUMHC=0.C
         SUMBC=0.0
         SUMBCT=0.0
         DO 80 J=1,REPEAT
               KOUNT=0
               T=0.0
               R=5C0.0
               NI=500.0
               OC=C.0
               hC=0.0
               BC=0.0
               BCT=0.0
               CALL LNORM(IX,DEVIAT,5000,1,0)
601            IF(T.GE.TIME) GO TO 60
                  KOUNT=KOUNT+1
                  T1=(NI-R)/ALAMDA(KOUNT)
                  IF(T1.GT.0.0) GO TO 61
                        TEMPNI=NI
                        OC=OC+A
                        XMU=ALAMDA(KOUNT)*LT(KOUNT)
```

```
      NI=NI-XMU
      IF(NI.GE.0.0) GO TO 611
            T2=TEMPNI/ALAMDA(KOUNT)
                BC=BC+PI*ABS(NI)
                BCT=BCT+PI*ABS(NI)*.5*(LT(KOUNT)-T2)
                HC=HC+(I*C*.5*TEMPNI*T2)
                GO TO 622
611   CONTINUE
            HC=HC+(I*C*.5*LT(KOUNT)*(TEMPNI+NI))
            GO TO 622
61    CONTINUE
      TEMPNI=NI
      OC=OC+A
      XMU=ALAMDA(KOUNT)*LT(KOUNT)
      NI=R-XMU
      IF(NI.GE.0.0) GO TO 621
            T2=R/ALAMDA(KOUNT)
            BC=BC+PI*ABS(NI)
            BCT=BCT+PI*ABS(NI)*.5*(LT(KOUNT)-T2)
            HC=HC+I*C*((.5*R*T2)+(.5*(TEMPNI+R)*T1))
            GO TO 622
621   CONTINUE
            HC=HC+((.5*(TEMPNI+R)*T1)+(.5*LT(KOUNT)*
     #         (NI+R)))*I*C
622   CONTINUE
      T=T+ABS(T1)+LT(KOUNT)
      IF(DEVIAT(KOUNT).GT.0.0) SIGN=1.0
      IF(DEVIAT(KOUNT).LT.0.0) SIGN=-1.0
C     INJECT UNBIASED ERRORS INTO FORECASTS
      LAMDA=SIGN*(MSE(K)**.5+1.0*DEVIAT(KOUNT))+
     #     ALAMDA(KOUNT)
      XMU=LAMDA*LT(KOUNT)
      TEMPQ=AMAX1(1.0,Q)
      TEMPNI=NI
      NI=TEMPNI+TEMPQ
      CALL INVENT(LAMDA,XMU,C,I,A,PI,SIG,Q,R)
      MULT=INT((R-TEMPNI)/TEMPQ+.99999)
      IF(MULT.GE.2) TEMPQ=FLOAT(MULT)*TEMPQ
      NI=TEMPNI+TEMPQ
      GO TO 601
60    CONTINUE
        SUMOC=OC/T+SUMOC
        SUMHC=HC/T+SUMHC
        SUMBC=BC/T+SUMBC
        SUMBCT=BCT/T+SUMBCT
80    CONTINUE
        AOC(K)=SUMOC/FLOAT(REPEAT)
        AHC(K)=SUMHC/FLOAT(REPEAT)
```

```
                ABC(K)=SUMBC/FLOAT(REPEAT)
                ABCT(K)=SUMBCT/FLOAT(REPEAT)
                ATVC(K)=AOC(K)+AHC(K)+ABC(K)
                ATVCT(K)=AOC(K)+AHC(K)+ABCT(K)
100       CONTINUE
          WRITE(2,600) (MSE(LL),LL=1,DELTAS)
          WRITE(2,600) (AOC(LL),LL=1,DELTAS)
          WRITE(2,600) (AHC(LL),LL=1,DELTAS)
          WRITE(2,600) (ABC(LL),LL=1,DELTAS)
          WRITE(2,600) (ABCT(LL),LL=1,DELTAS)
          WRITE(2,600) (ATVC(LL),LL=1,DELTAS)
          WRITE(2,600) (ATVCT(LL),LL=1,DELTAS)
          STOP
600       FORMAT(7F10.2)
          END
C*************************************************************************
          SUBROUTINE INVENT(LAMDA,XMU,C,I,A,PI,SIG,Q,R)
          REAL     LAMDA,XMU,C,I,A,PI,SIG,Q,R,QQ(100)
          INTEGER FLAG
          QW=SQRT((2.*C*LAMDA*A)/(I*C))
          CALL CHECK (LAMDA,A,I,C,PI,XMU,QW,QO,FLAG)
          IF(FLAG.EQ.1)GO TO 201
          CALL NORM(LAMDA,A,C,I,PI,QW,XMU,SIG,Q,R,Z,ETA)
          GO TO 202
201       Q=QO
          R=1.0
202       RETURN
          END
C**************************************************************************
          SUBROUTINE NORM(XL,A,C,XI,PI,QW,XM,S,Q,R,Z,ETA)
          DIMENSION QQ(100)
          REAL P/3.141593/
          PHI(X)=XK*EXP(-.5*X*X)
          XK=1./SQRT(2.*P)
          QQ(1)=QW
          I=2
10        XH=QQ(I-1)*XI*C/(PI*XL)
          XX=1.-XH
          CALL MDNRIS(XX,Z,IER)
          IF(IER.EQ.129)RETURN
          ORD=PHI(Z)
          ETA=ORD-Z*XH
          QQ(I)=SQRT((2.*XL*(A+(PI*S*ETA)))/(XI*C))
          DIF=ABS(QQ(I)-QQ(I-1))
          IF(DIF.LE.0.001)GO TO 20
          IF(I.EQ.100)GO TO 20
          I=I+1
          GO TO 10
```

```
20    Q=QQ(I)
      R=XM+S*Z
      RETURN
      END
C***********************************************************************
      SUBROUTINE CHECK(XL,A,XI,C,PI,XMU,QW,Q,FLAG)
      XX=(PI*XL)/(XI*C)
      Q=SQRT(2.*XL*(A+(PI*XMU))/(XI*C))
      IF(Q.GE.XX)GO TO 10
      FLAG=0
      RETURN
10    IF(QW.LE.XX)GO TO 20
      FLAG=1
      RETURN
20    CONTINUE
      FLAG=0
      RETURN
      END
```

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